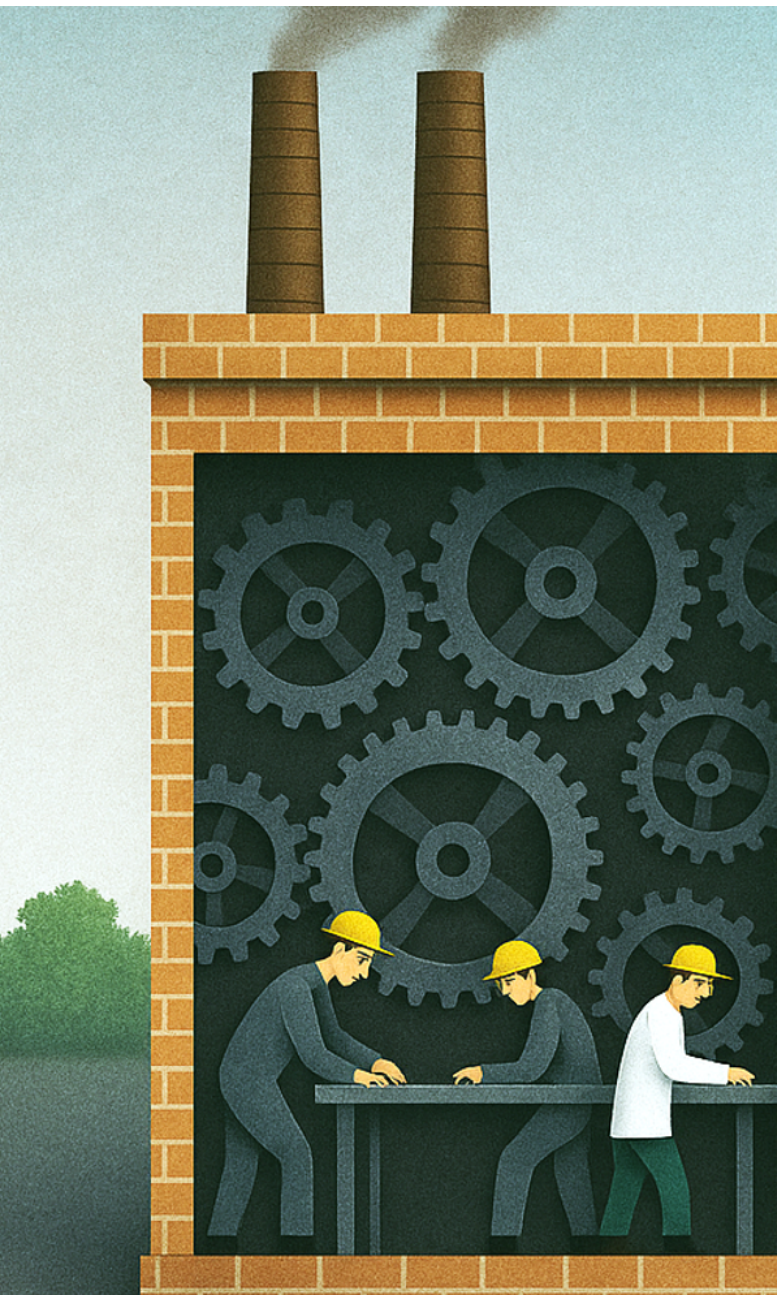


Navigating the Twin Transition for the Dutch high-tech manufacturing sector

Designing a decision-support tool to align digital innovation with sustainability goals



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innovation with sustainability goals

by

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"Our biggest challenge in this new century is to take an idea that seems abstract – sustainable development – and turn it into a reality for all the world's people."
Kofi Annan

Executive summary

The Dutch high-tech manufacturing sector faces the complex challenge of managing two deeply interconnected transitions: digital transformation and sustainability. This “Twin Transition” must reconcile the need to maintain global technological leadership and ambitious national sustainability targets for 2040 in combination with compliance with the Corporate Sustainability Reporting Directive (CSRD) that came into force in January 2024. While these transitions offer opportunities for mutual reinforcement, their relationship is complex. Digital technologies can support sustainability goals, but can also introduce environmental, social and economic impacts that conflict with sustainability initiatives.

This research identifies a critical gap in the existing literature and industry practice: the absence of an integrated decision-support tool linking digital maturity and sustainability performance, tailored to the specific needs of the Dutch high-tech manufacturing sector. Therefore, the main research question is: *What decision-support tool can be designed to support Dutch high-tech manufacturing companies to simultaneously improve their digital capabilities and sustainability performance in line with the CSRD?*

Using Design Science Research methodology, this study progressed through four phases: problem explication, requirement definition, design & development, and demonstration & evaluation. A structured literature review and eight expert interviews identified ten key implementation challenges. Four challenges were selected to be addressed in the tool development: high implementation costs with unclear returns, limited visibility into sustainability impacts of digital technologies, lack of sector-specific transition pathways, and absence of frameworks for quantifying trade-offs between digital and sustainability goals.

Requirements analysis through a second literature review and five user interviews established functional, structural, and contextual specifications using the MoSCoW prioritization framework. The resulting tool integrates three components: a comprehensive survey capturing company-specific Environmental, Social, and Governance (ESG) priorities and maturity baselines, a visual Twin Transition maturity model mapping current capabilities against target states across People, Process, and Policy dimensions, and a recommendation dashboard suggesting appropriate digital manufacturing technologies based on sustainability impact and implementation complexity. The tool adapts an existing maturity model by aligning ESG dimensions with digital transformation elements. Digital technologies are positioned across five maturity levels (descriptive, diagnostic, predictive, prescriptive, adaptive) with corresponding sustainability contributions assessed through Environmentally Extended Input-Output Analysis and MSCI ESG materiality mapping.

The tool functions as a decision-support tool by creating awareness of interconnections between digital and sustainability initiatives, enabling companies to navigate complex trade-offs through structured dialogue rather than providing prescriptive solutions.

Demonstration sessions with three consultants working with Dutch high-tech manufacturing clients and one manufacturing company validated the tool’s effectiveness in bridging departmental silos and facilitating strategic conversations around Twin Transition decision-making. Participants confirmed its usefulness for creating shared understanding between sustainability, technology, and operations teams, with the tool serving as a “conversation starter” that translates abstract strategic aspirations into concrete operational considerations tailored to each company’s specific context.

This research advances Twin Transition theory by delivering the first sector-specific integrated framework that explicitly links digital maturity levels with concrete ESG outcomes, moving beyond the binary

treatments common in current literature where digital and sustainability transformations are either separated or only superficially connected. Methodologically, the study demonstrates how a systematic DSR approach can bridge the persistent gap between theory and practice, offering a clear template for translating conceptual Twin Transition ideas into usable industry tools. The integration of quantitative impact assessment through EEIOA with stakeholder-driven requirement development represents progress beyond approaches that rely solely on generic frameworks or expert opinion. From an Industrial Ecology perspective, the study extends the field's traditional focus on physical resource flows to include the hybrid physical-digital nature of modern industrial systems. This research furthermore reinforces the insight that digital technologies are not inherently sustainable or unsustainable, but depend on how they are embedded in specific organizational contexts.

Practically, the tool gives Dutch high-tech manufacturers a concrete way to align digital transformation efforts with sustainability goals while staying compliant with CSRD requirements. By providing a structured, evidence-based framework for cross-functional discussion, the tool helps companies move beyond fragmented initiatives towards integrated strategies, making hidden trade-offs visible and creating a shared language for collaboration.

The research also highlights clear limitations. Many Twin Transition challenges are inherently complex, that cannot be fully addressed by structured tools alone. Therefore, methodological advances are needed to better handle the emergent, political, and cultural dynamics that shape real-world organizational change. Additionally, bottom-up studies on how digital-sustainability integration evolves organically within firms, and cross-national comparisons of how policy and institutional contexts influence outcomes, will be critical for building a deeper understanding of the Twin Transition in practice.

Additionally, future research should focus on expanding this approach to other sectors and to small and medium-sized enterprises (SMEs) to improve generalizability. There is also a need for deeper lifecycle and system boundary analyses that address rebound effects and absolute resource consumption. Multi-cycle DSR frameworks could test and refine such decision-support tools longitudinally in real settings.

In sum, this research demonstrates that the Twin Transition can be made more actionable through sector-specific, evidence-based decision-support tools, but only within clear limits. While digital solutions can enable efficiency gains, they alone cannot deliver full sustainability. A more radical sustainability transformation depends on aligning data, technology, governance, organizational culture, and policy frameworks.

Keywords: Twin Transition, high-tech manufacturing, Industry 4.0, CSRD, design science research, decision-support tool, maturity model.

Preface

About a year ago, I imagined the outline of my graduation project. Although the precise research questions had not yet been defined, I was determined to integrate the digital transition into the Industrial Ecology perspective on sustainability and to deliver a practical outcome. Now, I am pleased to introduce a thesis that brings those intentions together and reflects the values I carried into my time at TU Delft.

My master's in Industrial Ecology showed me that sustainability is a system whose parts only make sense when viewed as a whole. Management of Technology then taught me how digitalization and data can accelerate change when guided by solid business thinking. This thesis joins those lessons in a domain that has interested me since my bachelor in Applied Physics: the Dutch high-tech sector. In many ways, much of what I learned at TU Delft comes together in this one project.

The research explores how digital manufacturing technologies influence sustainability performance across different stages of digital maturity. By highlighting both the benefits and the trade-offs, it offers a balanced view. The practical outcome is an academically grounded decision-support tool that supports sustainability and manufacturing teams in Dutch high-tech in their conversations, find common ground, and decide on their next steps.

I am grateful to the many people who guided and supported me. In our earliest meetings Jolien Ubacht, my first supervisor, helped turn a wide collection of ideas into a clear, workable plan by asking the strategic questions that refined my scope and objectives. As the project matured, her insistence on academic rigor pushed me to think critically about which frameworks and methods would truly deepen the analysis. Throughout, she kept me anchored in solid theory while challenging me to deliver results that matter in practice. Linda Kamp, my second supervisor, encouraged me to step back, question my assumptions, and strengthen the narrative. At Accenture, Lukas Klaiber welcomed me, shared his enthusiasm as a great sparring partner, and opened his network when I needed expert input. I also want to thank my Accenture colleagues for their practical advice and the interview participants who generously shared their insights into Dutch high-tech manufacturing.

My family has been a constant source of encouragement and practical support throughout this journey, offering both reassurance and timely assistance whenever it was most needed. Finally, to my friends at TU Delft and beyond: the conversations, idea exchange, and coffee breaks made this journey not only productive but enjoyable.

Completing this thesis closes my MSc. Industrial Ecology chapter and inspired me to keep exploring the intersection of digital innovation and sustainability in my forthcoming Management of Technology research.

*Marie-Anne de Gier
Delft, July 2025*

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Acronyms

AHP	Analytical Hierarchy Process
AI	Artificial Intelligence
APC	Advanced Process Control
APS	Advanced Planning and Scheduling
AR	Augmented Reality
BOM	Bill of Materials
CBA	Consumption-Based Accounting
CLD	Causal Loop Diagram
CMM	Combined Maturity Model
CNC	Computer Numerical Control
COD	Chemical Oxygen Demand
CPS	Cyber-Physical System
CRMA	Critical Raw Materials Act
CSRD	Corporate Sustainability Reporting Directive
CS3D	Corporate Sustainability Due Diligence Directive
DCS	Distributed Control System
DESI	Digital Economy and Society Index
DHTM	Dutch High-Tech Manufacturing
DMM	Digital Maturity Model
DSR	Design Science Research
DSS	Decision Support System
EDA	Electrodermal Activity
EEIOA	Environmentally Extended Input-Output Analysis
ERP	Enterprise Resource Planning
ESG	Environmental, Social, and Governance
ESRS	European Sustainability Reporting Standards
EU	European Union
GDP	Gross Domestic Product
GHG	Greenhouse Gas
GRI	Global Reporting Initiative
GWP	Global Warming Potential
HMI	Human-Machine Interface
HREC	Human Research Ethics Committee
HTSM	High Tech Systems and Materials
IIoT	Industrial Internet of Things
IoT	Internet of Things
IOA	Input-Output Analysis
IP	Intellectual Property
IT	Information Technology
KPI	Key Performance Indicator
kt	Kilo ton
kWh	Kilowatt hours
LCA	Life Cycle Assessment

LE	Large Enterprise
LIMS	Laboratory Information Management Systems
MCDA	Multi-Criteria Decision Analysis
MCT	Manufacturing Control Tower
MES	Manufacturing Execution System
M&O	Manufacturing & Operations
MoSCoW	Must-have, Should-have, Could-have, Won't-have
MPC	Model Predictive Control
MRIO	Multi-Regional Input-Output
N/A	Not Applicable / Not Available
NL	Netherlands
NPD	New Product Development
OEE	Overall Equipment Effectiveness
OT	Operational Technology
PBA	Production-Based Accounting
PCB	Printed Circuit Board
PLC	Programmable Logic Controller
PLM	Product Lifecycle Management
PPP	People, Process, and Policy
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
QA	Quality Assurance
R&D	Research & Development
ROI	Return on Investment
SASB	Sustainability Accounting Standards Board
SCADA	Supervisory Control and Data Acquisition
SDG	Sustainable Development Goal
SMEs	Small and Medium-sized Enterprises
SPC	Statistical Process Control
SVHC	Substances of Very High Concern
t	ton
TBL	Triple Bottom Line
TJ	Terajoules
US	United States of America
VOC	Volatile Organic Compound

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1

Introduction

The European Commission has identified two major forces that will reshape industries: the green transition and the digital transition. The green transition arises from the urgent need to combat climate change and environmental degradation, formalized through international agreements such as the 2015 Paris Agreement and the European Green Deal. In contrast, the digital transition is driven by the opportunities technology offers for societal advancement and economic growth (Muench et al., 2022).

Although these transitions have the potential to reinforce each other, their relationship is complex. Digital technologies can help advance sustainability goals, but they can also create sustainability impacts that may undermine green initiatives. This complexity highlights the need for an integrated approach that carefully manages both transitions, focusing on understanding their interconnections, synergies, and potential conflicts (Muench et al., 2022).

European manufacturing companies face challenges in managing this Twin Transition. They are under increasing pressure to adapt their value chains to new environmental regulations and technological advances (van Erp and Rytter, 2023). This dual challenge is particularly evident in high-tech manufacturing, a sector characterized by constant innovation and a wide range of sustainability challenges, like high energy consumption, use of toxic chemicals, electronic waste generation and inclusion of diverse stakeholders (Lee et al., 2023).

Recent changes in the policy landscape further highlight the urgency of addressing these challenges. Sustainability policies are increasingly pressuring manufacturers to accelerate their environmental transitions, while industrial and innovation policies simultaneously encourage technological advancement. For example, the Corporate Sustainability Reporting Directive (CSRD), adopted in 2022, requires companies to report on their environmental impacts (e.g. energy use, GHG emissions, waste generation and treatment, etc.), social impacts (diversity and inclusion, fair compensation, health and safety, etc.) and governance impacts (ethical culture, mitigating conflicts of interest, anti-corruption, etc.) with more rigorous and standardized disclosure requirements across the European Union (EU) (European Parliament and the Council, 2022). Larger firms must comply from 2025 (covering 2024 data), with phased compliance for others. By early 2025, further adjustments have been proposed, such as the “Omnibus” amendments, a potential delay for the second wave of companies until 2028, acknowledging the administrative burden for firms new to sustainability reporting (European Commission, 2025a). In the Netherlands, the CSRD is being transposed into national law with updates to the Commercial Code and practical implementation guidance for companies (Rijksdienst voor Ondernemend Nederland (RVO), 2025).

Traditional linear production models are increasingly inadequate to address the growing levels of waste in high-tech manufacturing that harm the environment and create financial losses (Viniak et al., 2022). High-tech manufacturers also struggle with limited insight into their sustainability performance, further complicating compliance and stakeholder expectations for sustainable practices (Viniak et al., 2022). Without quick action to address their growing environmental impacts, high-tech manufacturers risk having their innovative products overshadowed by their environmental costs (Viniak et al., 2022).

Simultaneously, digital transformation in high-tech manufacturing has progressed significantly, but

is still incomplete. Although the sector's level of digitalization is slightly above average and many companies have moved beyond proof-of-concept to piloting digital solutions at specific sites, scaling these initiatives and achieving measurable benefits remains a challenge (Blanchet et al., 2020).

To support digital and sustainable innovation, recent EU industrial policy initiatives have been launched. The Green Deal Industrial Plan (2023) aims to strengthen clean-tech manufacturing by simplifying permitting procedures, increasing funding access, supporting skills development, and diversifying supply chains (European Commission, 2023b). Complementary frameworks such as the Net-Zero Industry Act (European Commission, 2024b) and the Critical Raw Materials Act (CRMA) (European Commission, 2020a) seek to improve access to critical materials and promote circular economy practices, with targets for domestic extraction and recycling by 2030. Moreover, the European Chips Act (2022–2023) addresses semiconductor shortages and aims to double Europe's chip production to 20% of the global share by 2030, backed by €43 billion in investments (European Commission, 2024a).

The Dutch high-tech manufacturing sector exemplifies these complex challenges. The sector has set ambitious goals for 2040, including achieving net-zero carbon emissions across operations, supply chains, and product use, as well as establishing nearly 100% circular value chains (van Kappen et al., 2023). These efforts focus on renewable energy adoption, improved product design, and CO₂ reuse systems (van Kappen et al., 2023).

At the same time, digital innovation remains a priority for the Dutch high-tech manufacturing sector, with initiatives such as the Dutch Smart Industry Implementation Agenda aimed at improving production efficiency and competitiveness (Martinetti et al., 2024). Although the digitalization of the Dutch manufacturing sector is above the EU average, it lags behind the Nordic countries, where 60% of companies are highly digitized, compared to 41% in the Netherlands (Yagafarova et al., 2024).

National innovation policies further support these ambitions. Through initiatives such as the Top-sector High Tech Systems and Materials (HTSM) platform, the Netherlands stimulates the integration of digitalization (e.g., Industry 4.0) and sustainability (e.g., circular manufacturing) into innovation roadmaps (Rijksdienst voor Ondernemend Nederland (RVO), 2024). The Dutch digitalization Strategy similarly emphasizes the adoption of technologies such as AI and digital twins to improve production efficiency and support climate goals (Nederland Digitaal, nd).

The interconnectedness of the Twin Transition challenges in the Dutch high-tech manufacturing sector is also evident. van Kappen et al. (2023) notes that technologies offer promising solutions for real-time CO₂ monitoring and circular economy practices. However, their implementation requires careful management, as these innovations also bring sustainability challenges, including increased energy consumption and resource use (van Baars et al., 2020).

1.1. Defining the Twin Transition

The Twin Transition concept describes how green and digital processes converge and depend on each other. According to the European Union, these are not separate challenges but connected transformations where "neither can succeed without the other," both essential for Europe's future (European Commission (2025b)). This concept shows how digital progress improves sustainability efforts, leading to greening both of and through IT and data (Hellemans and Oostervink, 2025).

In sustainability studies, researchers often distinguish between transitions and transformations. Transitions involve changes in social structures, institutions, and technologies within specific sub-systems. Transformations, however, refer to wider, society-level shifts. Researchers typically analyze transitions by looking at drivers and barriers, viewing them as more controlled processes. They study transformations by focusing on emerging patterns and outcomes that require adaptive responses (Hölscher et al., 2018).

Interestingly, research combining sustainability and digitalization does not maintain this distinction. A bibliometric analysis by Fatemi et al. (2025) of Twin Transition research shows that experts use "twin transition" and "twin transformation" interchangeably.

In this research, the Twin Transition definition does not present these two perspectives as mutually exclusive but rather as two sides of the same coin. The transition perspective guides the applied side of the work: it links practical challenges to practical solutions, offers a structured research path, and gives companies a measure of control as they choose suitable transition pathways. The emergent and

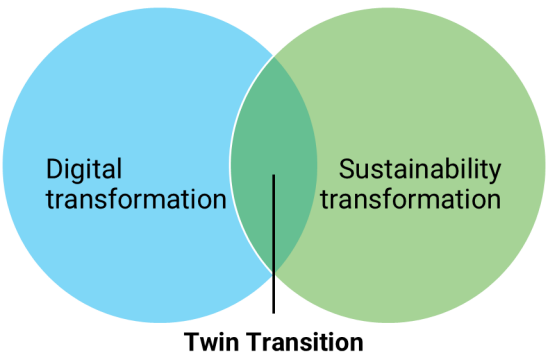


Figure 1.1: Definition of the Twin Transition as the intersection of the digital and sustainability transformations. Adapted from Hellemans and Oostervink (2025).

adaptive perspective serves the academic side, focusing on the wider complexity and changing context (such as shifts in the regulatory landscape) that lie beyond individual firms.

Thus, the Twin Transition here refers to a single, connected shift in the Dutch high-tech manufacturing sector. It merges company-level digital transformation and sustainability into one program, so advances in one reinforce the other. The idea is more than running two transitions in parallel. Digital technology should support sustainability performance (“greening by IT”). At the same time, any extra sustainability footprint from those same technologies must be monitored (“greening of IT”). Monitoring both effects supports trade-off identification and allows for converting them into positive synergies. Because digital and green goals interact, the Twin Transition is considered to be a complex strategic task that requires an integrated, approach to balance trade-offs and unlock shared benefits.

In the context of the EU’s definition of the Twin Transition, it is furthermore important to clarify what is meant by digital transition or transformation. Digital (business) transformation is understood as a strategic, organization-wide change process, in which digital technologies are not only used to optimize existing processes but serve as accelerators for rethinking and innovating value propositions, business models, and entire ecosystems (Vrana and Singh, 2021; Lang, 2021). This transformation involves organizational culture shifts, the development of new capabilities, and cross-sector collaborations.

It builds upon digitization (the technical conversion of analog information into digital formats to enable processing, storage, and transmission) and extends beyond digitalization, which focuses on improving or automating existing processes without altering the fundamental business model (Vrana and Singh, 2021; Lang, 2021). This is summarized visually in Figure 1.2.

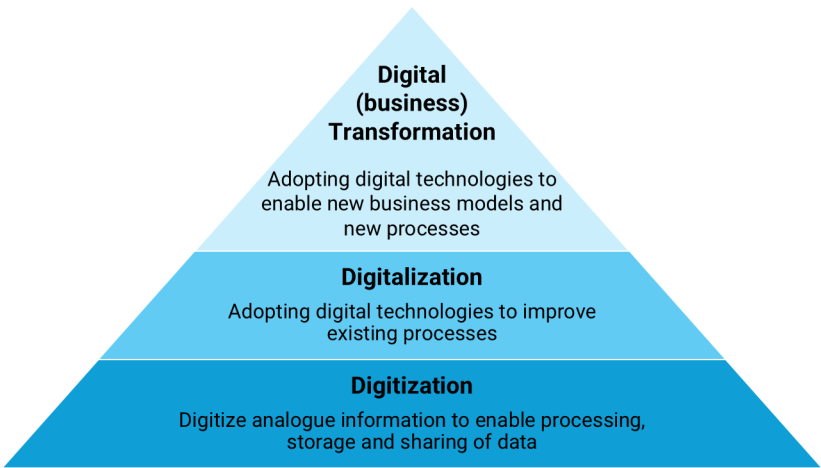


Figure 1.2: Definition of digital (business) transformation within the context of the Twin Transition, illustrating its relationship to digitalization and digitization. Adapted from Lang (2021).

1.2. Defining the Dutch high-tech manufacturing sector

The Dutch high-tech manufacturing industry is defined according to Eurostat's classification system, which categorizes manufacturing into four groups: high-technology, medium high-technology, medium low-technology, and low-technology. This report focuses on high-tech manufacturing and the upper segment of medium high-tech manufacturing (Velthuisen et al., 2024). Within high-tech manufacturing, the main subsectors include Machinery and Equipment, Electrical and Electronic Equipment, Medical Technology, Aerospace, and Other Transport Equipment.

Despite significant differences in products, volumes, and industries (detailed in Appendix A, Table A.1), Dutch high-tech subsectors share several fundamental manufacturing process characteristics. These similarities are based in the inherent demands of high-tech production, which prioritizes precision, quality, flexibility, and innovation. Across all subsectors, manufacturing processes are designed for extreme precision and zero-defect quality. Whether producing an ASML lithography system, a Philips MRI scanner, a NXP automotive chip, a GKN Fokker aircraft wing, or a Damen patrol vessel, manufacturers embed rigorous testing and validation into multiple stages of production to guarantee functional excellence and eliminate defects (ASML, 2020; Philips Healthcare, 2023; McKinsey & Company, 2019; GKN Fokker Technologies, 2025; Damen Shipyards Group, 2018).

High-tech manufacturing in the Netherlands also relies on the integration of multiple engineering disciplines, including mechanics, electronics, software, optics, and materials science. This interdisciplinary approach requires sophisticated planning, concurrent engineering, and close collaboration between specialized teams. Human expertise remains highly important, particularly in final assembly, testing, calibration, and troubleshooting (ASML, 2020; Velthuisen et al., 2024). Skilled labor complements automation, especially in the final production stages where flexibility, precision, and judgment are critical. For instance, ASML cleanroom technicians require optics and precision assembly skills, Philips production engineers manage complex regulatory documentation, and Fokker aerospace technicians are certified in advanced composite layups and welding (ASML, 2020; Philips Healthcare, 2023; GKN Fokker Technologies, 2025; McKinsey & Company, 2019).

Compared to traditional mass manufacturing, Dutch high-tech manufacturers typically produce smaller quantities, ranging from dozens to a few thousand units per year, handle greater product variation through customized configurations, which is referred to as high-mix, low-volume production (McKinsey & Company, 2019). These manufacturers operate with longer production cycles, sometimes requiring six to twelve months to complete a product (Velthuisen et al., 2024).

1.3. Scoping decisions

This study focuses exclusively on large companies within the Dutch high-tech manufacturing sector. SMEs are excluded because the CSRD primarily applies to large companies at the time of this study (with phased compliance starting in 2025), and large companies significantly influence sustainability standards throughout their supply chains, including SME suppliers (ASML Holding N.V., 2025a). Focusing on large enterprises therefore offers greater strategic impact and research relevance for understanding Twin Transition implementation. Large companies are defined according to the European Commission's criteria, meaning firms with more than 250 employees and an annual turnover exceeding €50 million or a balance sheet total above €43 million (European Commission, 2020b). Examples of companies included in this study are:

- ASM International (ASMI), specializing in atomic layer deposition technology for semiconductor device fabrication;
- ASML, which designs and manufactures EUV lithography systems for semiconductor chip production;
- BE Semiconductor Industries (BSI), focused on die attach, packaging, and plating equipment for the semiconductor industry;
- NXP Semiconductors, designing semiconductors and microchips for automotive, industrial, mobile, and IoT applications;
- Omron Europe BV, manufacturing automation technology, electronic components, and healthcare equipment;
- Philips, known for diagnostic imaging, patient monitoring, and digital healthcare solutions;

- Prodrive Technologies, designing high-tech electronics, software, and mechatronic systems for sectors like automotive, semiconductor, and medical industries;
- Siemens Nederland N.V., offering products and services in electrification, automation, and digitalization;
- Signify, a producer of energy-efficient lighting systems and services;
- Thales Nederland, developing defense and security systems, particularly naval radar and cyber-security solutions; and
- Thermo Fisher Scientific, providing analytical instruments, laboratory equipment, and software for scientific research and healthcare.

Furthermore, this study focuses on the direct sustainability impacts from sources owned or controlled by a Dutch high-tech manufacturing company (Scope 1) (Kenway et al., 2023). It also includes the indirect impacts from the generation of purchased energy that the company uses (Scope 2). However, it does not cover Scope 3, which are the indirect impacts that occur outside the company's own operations, such as those caused by suppliers or customers. Therefore, the boundaries of this research are limited to the company's internal manufacturing activities. In Chapter 5 outlines the exact sustainability impacts that are taken into account.

Although a substantial part of the overall sustainability impact occurs in the supply chain, the direct influence that Dutch high-tech manufacturers can exert over their suppliers is often structurally limited (McKinsey & Company, 2019). These companies are highly dependent on specialized components sourced through long-term, strategic partnerships, such as ASML's decades-long collaboration with Carl Zeiss (ASML, 2025). This dependency makes supplier switching or enforcing new sustainability standards difficult, in contrast to traditional manufacturers who often have more flexibility in supplier choice. As a result, targeting the companies' own manufacturing processes offers the most immediate and actionable opportunity for sustainability improvement. This focus is further supported by internal discussions at Accenture, confirming that manufacturers have significantly more control, ownership, and innovation capacity within their own operations than across their supply networks. Consequently, this study concentrates on the direct sustainability impacts of the Dutch high-tech manufacturing process and investigates how digital technologies can be leveraged to drive improvements within this scope.

Moreover, in the context of the Twin Transition, this study focuses on process sustainability rather than product sustainability within the Dutch high-tech manufacturing sector. This choice reflects the more direct and immediate impact of the Twin Transition on manufacturing processes. In contrast, applying the framework to products is more complex due to long innovation cycles, strict regulations, and technical performance requirements. Redesigning products for sustainability often requires major changes in materials, architecture, or functionality, which digital technologies alone cannot easily achieve. Additionally, many high-tech products are highly customized and produced in low volumes, making it difficult to scale product-level sustainability improvements. Focusing on process sustainability, therefore, better leverages digital technologies for immediate, scalable environmental gains and aligns with the operational control manufacturers already possess.

1.4. Current research on the Twin Transition in manufacturing

In recent years, academic interest in both the digitalization of manufacturing and sustainability performance has grown rapidly (Fatemi et al., 2025). However, research that explores how these two areas intersect (particularly in the context of high-tech manufacturing) remains limited. While the fields are evolving, they often do so in parallel rather than in coordination, leaving a significant gap in integrated approaches.

1.4.1. Digital transformation of manufacturing

Digital transformation is a key driver in modern manufacturing, captured by the concept of digital maturity. Digital maturity measures an organisation's ability to adopt and integrate advanced digital technologies (Kupriyanova et al., 2020), progressing from basic digital awareness to autonomous, data-driven systems (Colli et al., 2018). It spans dimensions such as governance, technology, connectivity, value creation, and capability, which together enable systematic digital advancement (Kupriyanova et al., 2020;

Colli et al., 2018; Senna et al., 2023).

Industry 4.0 context

Industry 4.0, launched in 2011 as a strategic initiative by the German government, represents a transformative shift in manufacturing (Frank et al., 2019). Its goal is to create real-time, interconnected production systems that enhance efficiency, reduce defects, and enable flexible manufacturing that adapts to rapidly changing demands (Dalenogare et al., 2018; van Baars et al., 2020). This transformation is made possible by integrating technologies such as the Industrial Internet of Things (IIoT), cloud computing, and augmented reality (AR) (Frank et al., 2019; Machado et al., 2020). For example, IIoT enables the collection of real-time data from machines and sensors on the shop floor. This allows for monitoring production conditions and optimizing machine use (Frank et al., 2019).

Industry 4.0 technologies fall into two categories: base technologies, providing digital infrastructure, and front-end technologies, addressing operational needs in manufacturing, products, and supply chains (Frank et al., 2019; Ching et al., 2022). In line with the scoping decision of the focus on the manufacturing process itself, the Industry 4.0 technologies taken into account in this study are digital manufacturing technologies. These are defined as software or digital systems that manage, monitor and optimize production (da Silva et al., 2019). Digital manufacturing tools are focused on data flow, control, automation and connectivity.

Gartner's 2024 Hype Cycle for advanced technology adoption in the manufacturing sector suggests that full digital transformation will be a long-term transition, as key Industry 4.0 technologies are expected to take 5-10 years to mature (Shikanai et al., 2024). In addition, the emergence of integrated solutions, shows that successful digitalization requires the development of a comprehensive ecosystem rather than the implementation of isolated technologies (Shikanai et al., 2024).

Digital Maturity Models

Research on digital maturity models (DMMs) has expanded with the rise of Industry 4.0 (Grooss et al., 2022). DMMs offer structured frameworks to assess organisational readiness to adopt digital technologies, typically outlining stages from basic awareness to full autonomy (Colli et al., 2018; Kupriyanova et al., 2020; Senna et al., 2023). However, DMMs face challenges such as inconsistent definitions, data collection issues, and limited empirical validation, reducing their generalisability (Grooss et al., 2022). Many focus mainly on organisational aspects, neglecting technological drivers and causing strategic misalignment (Grooss et al., 2022). Recent models increasingly use hybrid approaches combining qualitative and quantitative methods (Senna et al., 2023), helping organisations benchmark progress and define goals. Still, there remains a need for adaptable, validated, sector-specific models, particularly for high-tech manufacturing (Kupriyanova et al., 2020; Grooss et al., 2022).

Shift towards sustainable manufacturing

While increasing productivity, Industry 4.0 has been criticised for overlooking sustainability and socio-environmental concerns (Ching et al., 2022), which lead to the rise of Industry 5.0, which incorporates human-centric and environmental priorities alongside innovation (Ching et al., 2022; Martín-Gómez et al., 2024).

Sustainable manufacturing incorporates economic, environmental, and social goals, following the 'triple bottom line' principle (Martín-Gómez et al., 2024). It seeks to minimize environmental impacts, conserve resources, and enhance stakeholder well-being while maintaining competitiveness (Machado et al., 2020; Ching et al., 2022). Unlike traditional green or lean approaches, it addresses the entire product life cycle and adapts to technological and market changes (Moldavska and Welo, 2017). Aligned with circular economy principles, it promotes closed-loop systems through reuse, remanufacturing, and recycling. Strategies such as slowing, closing, and narrowing resource loops rely on technologies like additive manufacturing, predictive maintenance, and IoT (Antikainen et al., 2018; Titmarsh et al., 2020).

1.4.2. Sustainability performance models

Several frameworks assess sustainability performance of (manufacturing) companies by evaluating economic, environmental, and social impacts. These models typically define maturity levels to guide companies' progress toward sustainability. Eisner et al. (2022), expanding on Müller and Pfleger (2014), proposed a six-level framework, from basic compliance (Initial) to the adoption of circular economy

principles (Visionary). Although it promotes integration of sustainability into operations through information systems, it does not explicitly consider the influence of digital maturity or the specific context of high-tech manufacturing. This model is visually summarized in Figure 1.3.

Ivascu (2020) introduced a five-level framework linking sustainable manufacturing to Industry 4.0. It progresses from stakeholder engagement and financial metrics to material optimization, life cycle value recovery, and adoption of the 9Rs (e.g., reuse, recycle, redesign). While highlighting Industry 4.0, it treats digital maturity as a step within sustainability rather than a broader enabler across the triple bottom line. This model is also visually summarized in Figure 1.3.

Overall, existing models either broadly address corporate sustainability or view digital maturity as secondary, without fully exploring its role in enhancing economic, social, and environmental outcomes.

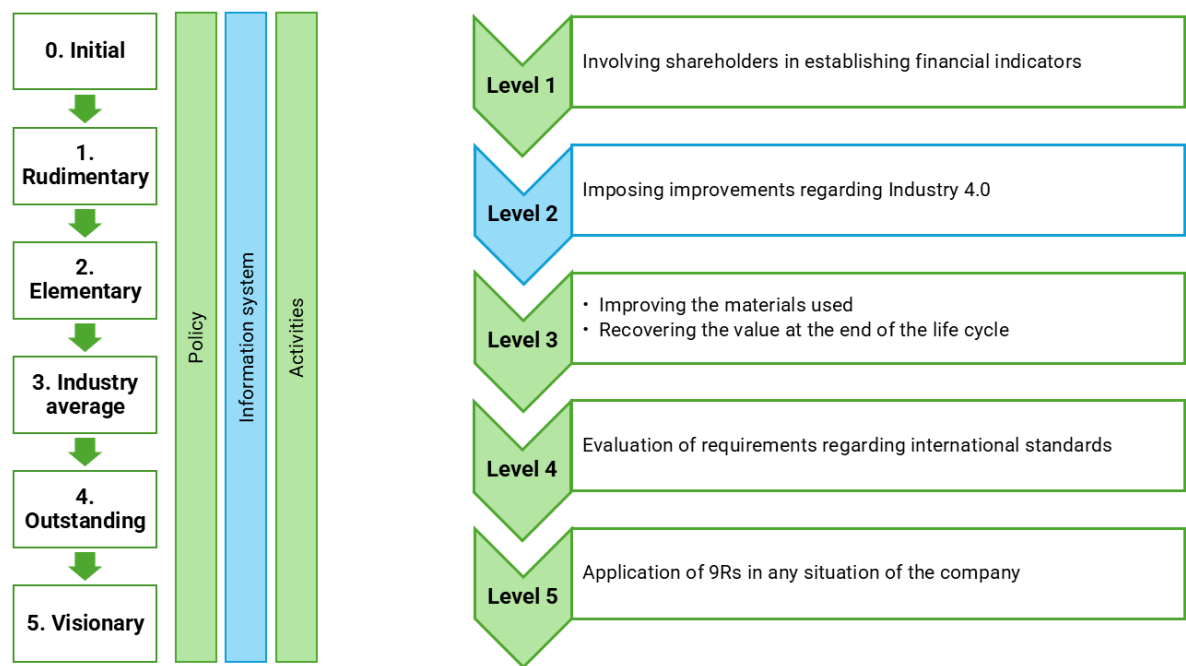


Figure 1.3: Visual interpretations of the sustainability performance models by Eisner et al. (2022) (left) and by Ivascu (2020) (right). In both models, the maturity levels are illustrated, with the digital component specifically highlighted in blue.

1.4.3. Digitalization and sustainability: convergence and challenges

While Industry 4.0 technologies can support triple bottom line objectives (economic, environmental and social), their implementation can also have negative sustainability impacts. Table A.2 in Appendix A provides an overview of potential sustainability opportunities and potential drawbacks across environmental, social and economic dimensions. From Table A.2 in Appendix A, it is clear that Industry 4.0 technologies can lead to significant improvements in operational efficiency, particularly in energy use and materials management, as well as extending the life of assets through better maintenance. In terms of social sustainability, these technologies can improve the safety of workers, and in terms of economic sustainability, they offer cost savings.

However, these benefits come with significant trade-offs. While Industry 4.0 technologies can reduce energy consumption through efficiency gains, they also tend to increase energy consumption, as many of these systems are inherently energy-intensive, as shown for several technologies in Table A.2 in Appendix A. Research by Bildirici and Ersin (2023) on the adoption of Industry 4.0 technologies at the country level shows that, in the long run, these technologies often contribute to increased CO₂ emissions. This is due to their indirect impact on energy consumption, which increases emissions. This finding highlights the importance of quantifying both opportunities and trade-offs, to accurately assess the sustainability impact of increased digital maturity.

Current practices for implementing Industry 4.0 technologies show a strong bias toward improving

productivity, often at the expense of broader sustainability outcomes (Kopeinig et al., 2024). While economic sustainability is one of the more immediate benefits of Industry 4.0, if applied effectively, these technologies also have the potential to support environmental and socio-economic sustainability (Ghobakhloo, 2020). Specifically, greater manufacturing efficiency, cost savings, and improved profitability can contribute to better environmental management and more efficient resource use across manufacturing networks, ultimately aiding environmental protection and emissions reduction (Ghobakhloo, 2020).

To better understand and balance the trade-offs between Industry 4.0 technologies and sustainability goals, further research is needed, particularly through case studies that assess both the systemic benefits and negative impacts on manufacturing companies (Fritzsche et al., 2018). Although some integrated models attempt to address this gap, they still fall short in important ways.

For example, the Twin Transformation Butterfly model by Christmann et al. (2024) outlines the high-level capabilities needed for combined digital and sustainability transformations. However, it does not provide a method for assessing a company's current position within these transitions, nor does it offer concrete steps for progression. Additionally, it is not specifically tailored to the unique challenges faced by Dutch high-tech manufacturing as explained by Yagafarova et al. (2024) and van Kappen et al. (2023) above.

Similarly, the road mapping methodology for the Twin Transition developed by Spaltini et al. (2024b) focuses on applying digital solutions to achieve sustainability goals at the plant level. While valuable, this model overlooks the possibility that digitalization can also lead to negative sustainability impacts. Moreover, the framework by Spaltini et al. (2024b) is designed for the food and beverage manufacturing sector, a more traditional manufacturing industry with different challenges compared to the high-tech manufacturing sector.

The Twin Transition Maturity model by Meuser et al. (2024) offers a maturity assessment tool for manufacturers aiming to improve sustainability. However, it has a very narrow focus, concentrating only on the reduction of scope 1 and scope 2 carbon emissions. It does not consider wider environmental impacts, nor does it address the social and economic dimensions of sustainability. Additionally, this model only assesses the current state of Twin Transition progress without providing guidance on next steps. Like the other models, it is not adapted to the specific needs of the Dutch high-tech manufacturing sector.

This fragmented landscape highlights a clear need: there is currently no sector-specific tool that integrates assessments of both digital maturity and sustainability performance, particularly in light of evolving regulations such as the CSRD. Without such a framework, high-tech manufacturers lack the guidance necessary to make informed decisions, weigh trade-offs, and identify synergies between digital innovation and sustainable development.

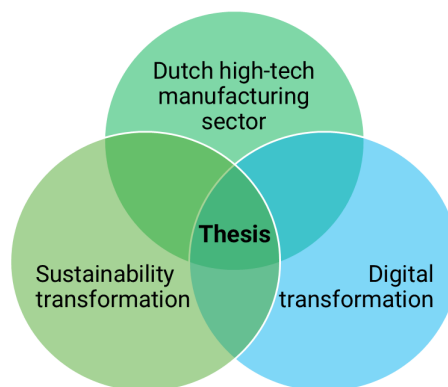


Figure 1.4: Visualization of the three domains that constitute this research, in the development of a decision-support tool for the Dutch high-tech manufacturing sector to support the Twin Transition.

This research aims to fill the gap by developing a decision-support tool tailored to the Dutch high-tech manufacturing sector. The tool bridges the digital and sustainability domains by facilitating strategic

conversations on using digital technologies for sustainability purposes. It helps companies understand the broader, systemic sustainability impacts of digital manufacturing and supports awareness, prioritization, and decision-making to align digital innovation with sustainability goals.

1.4.4. Multi-level analysis

To effectively analyze the complexity of the Twin Transition, this research adopts a multi-level framework that interconnects macro, meso, and micro-level perspectives. This approach ensures that the decision-support tool aligns high-level policy demands with sector-specific needs and actionable interventions on the factory floor. This is visualized in Figure 1.5.

- At the **macro-level**, the research considers the overarching forces and regulatory landscapes influencing the digital and sustainability transitions. The thesis is set within the context of key European legislation, such as the Corporate Sustainability Reporting Directive (CSRD), and national initiatives like the Dutch Smart Industry Implementation Agenda. This level establishes the "why" behind the Twin Transition and outlines the future context that companies must navigate.
- The macro-level regulations and forces create **meso-level** challenges for the Dutch high-tech manufacturing sector. Therefore, this level of analysis focuses on the sector as a whole, identifying sector-wide implementation challenges for the Twin Transition. It details the most relevant digital manufacturing technologies and sustainability impacts (as defined by the ESRS) for the Dutch high-tech manufacturing sector. For example, it clarifies which environmental, social, and governance (ESG) impacts are most important given the specific characteristics of the sector.
- These meso-level challenges, technologies, and sustainability impacts drive the need for **micro-level solutions**. At this level, the analysis specifies the granular details of how certain digital manufacturing technologies can be leveraged for sustainability, while also considering their potential negative impacts. For example, it specifies how technologies like Enterprise Resource Planning (ERP) systems, SCADA, and Augmented Reality (AR) function within a high-tech manufacturing context and what they can contribute to, or detract from, specific sustainability goals, such as reducing energy consumption (ESRS E1-5), GHG emissions (ESRS E1-6), or the use of toxic chemicals (ESRS E2-5).



Figure 1.5: Visualization of the multi-level analysis throughout the thesis research.

1.5. Research question

The main research question guiding this research can therefore be formulated as:

What decision-support tool can be designed to support Dutch high-tech manufacturing companies to simultaneously improve their digital capabilities and sustainability performance in line with the Corporate Sustainability Reporting Directive (CSRD)?

To explore this main research question, the research delves into five sub-research questions:

1. What are the challenges faced by Dutch high-tech manufacturing companies in implementing the Twin Transition?
2. What functional, structural and contextual requirements must the decision-support tool meet to support the Dutch high-tech manufacturing sector in addressing the identified Twin Transition

implementation challenges?

3. What is the corresponding decision-support tool that integrates the identified requirements to support Dutch high-tech manufacturing companies in implementing the Twin Transition?
4. How does the integrated decision-support tool for the Dutch high-tech manufacturing sector perform when demonstrated to intended target users?
5. How can the proposed decision-support tool be improved, based on the results of the demonstration phase, to ensure that it is an effective decision support tool for the Dutch high-tech manufacturing sector to simultaneously improve its digital and sustainability capabilities?

1.6. Context of the thesis: Accenture Industry X

This thesis is being carried out via a Graduation Internship at Accenture Industry X, within the Manufacturing & Operations (M&O) department. Accenture Industry X focuses on the digital transformation of industrial and manufacturing organizations by combining digital technologies with engineering and production expertise. The group helps clients improve how products are designed, manufactured, and maintained by leveraging digital manufacturing technologies.

Within Industry X, the Manufacturing & Operations department supports clients in optimizing their production environments. This includes enhancing operational efficiency, safety, and effectiveness through data-driven solutions and integrated technologies. The department works on projects ranging from early-stage engineering to the deployment of digital tools that enable smarter, more connected manufacturing processes.

This environment provides a relevant and practical context for this research, which aims to support Dutch high-tech manufacturing companies in implementing the Twin Transition. In addition, the internship offers access to internal Accenture resources, including grey literature, project documentation, and reference materials that are not publicly available. It also enables close collaboration with domain experts within Accenture and their broader network of clients and partners. This access to both practical expertise and proprietary knowledge represents a valuable opportunity for conducting applied research in a real-world setting, particularly in a field where such insight is not always readily accessible.

Research approach & methodology

This study employs the Design Science Research (DSR) methodology, as outlined by Johannesson and Perjons (2014), to develop a decision-support tool that is both theoretically grounded and practically validated, aimed at facilitating the implementation of the Twin Transition in Dutch high-tech manufacturing companies.

This chapter briefly introduces DSR, explains how the five research phases are applied in this study, and shows how each phase answers one or more sub-research questions. Next, the chapter details the data collection and analysis methods that support one or more of the DSR phases. The chapter ends with a research flow diagram summarizing the research process and methodology.

2.1. Design Science Research (DSR)

Design Science Research (DSR) focuses on creating and evaluating artifacts that address practical problems, bridging theory and practice (Johannesson and Perjons, 2014). It is particularly suited to research that not only studies phenomena, but also develops practical artifacts (tools, models or frameworks) to advance academic knowledge and industry practice (Johannesson and Perjons, 2014).

In contrast to case-specific solutions, DSR aims to produce broadly applicable knowledge by meeting three key requirements: (1) a systematic and robust methodology to ensure reliable results, (2) grounding findings in existing knowledge for originality and soundness, and (3) effective communication of results to researchers and practitioners (Johannesson and Perjons, 2014). This is particularly important in a context such as the high-tech manufacturing sector in the Netherlands, where digital transformation and sustainability are currently limited by organizational factors (Yagafarova et al., 2024).

2.2. Overview of the DSR phases

The DSR process includes five main phases. Each phase is linked to one or more sub-research questions. Below is a high-level overview of each step, with further details provided in the chapters that follow.

2.2.1. Phase 1: Explicating the problem

The first phase focuses on understanding the core problem that this research aims to address. In the context of the Twin Transition, Dutch high-tech manufacturing companies are expected to improve both their digital capabilities and sustainability performance. However, combining these two goals is not straightforward. The relationship between digital transformation and sustainability is often complex, with unclear trade-offs, benefits, and implementation pathways.

To answer **sub-research question 1**, *What are the challenges faced by Dutch high-tech manufacturing companies in implementing the Twin Transition?*, two methods were applied:

- A structured literature review was conducted to identify common challenges related to imple-

menting the Twin Transition in the manufacturing sector. As there is limited academic research focused specifically on the Dutch high-tech manufacturing sector, the review looked more broadly at manufacturing in general. The PRISMA method was used to ensure a systematic and transparent selection of relevant papers.

- The findings from the literature review were then tailored to the Dutch high-tech context through a series of eight semi-structured expert interviews. Interviewees included representatives from academia, industry, and umbrella organizations. To structure the interviews, participants were first asked to rank the importance of the challenges identified in the literature through a survey. The interviews then explored these ranked challenges in greater detail.

The combination of literature and expert interviews ensured that the challenges identified were both academically grounded and practically relevant. This phase resulted in a clear and well-justified problem statement, which forms the foundation for the design of the decision-support tool in later phases.

2.2.2. Phase 2: Defining the requirements

In the second phase, the key challenges from Phase 1 were translated into specific design requirements for the decision-support tool. These requirements are grouped into three categories:

- Functional requirements: what the tool should do to address the identified challenges.
- Structural requirements: how the tool should be built and what components it should include.
- Contextual requirements: what the intended users need from the tool in their day-to-day practice.

This phase answers **sub-research question 2**: *What functional, structural and contextual requirements must the decision-support tool meet to support the Dutch high-tech manufacturing sector in addressing the identified Twin Transition implementation challenges?*

The following steps were taken to define and verify these requirements:

- The identified challenges from the first DSR phase were translated into functional requirements.
- A literature review was conducted to identify how existing tools and models have addressed similar functional requirements. This provided a basis for the structural requirements.
- Collaboration with Accenture Industry X helped define the intended user profile for the tool. These users are typically consultants or corporate decision-makers who support large Dutch high-tech manufacturing firms.
- Five additional interviews were conducted with professionals who matched the user profile. During these interviews, participants were asked to review and prioritize the proposed functional, structural, and contextual requirements. Their feedback was used to refine the list and focus the tool's design on features that were both valuable and feasible.

By the end of this phase, a clearly defined and validated set of requirements was established to guide the development of the decision-support tool.

2.2.3. Phase 3: Design and development

In the third phase, the decision-support tool was designed and built using the insights and requirements from Phase 2. The tool is structured around three main elements:

1. A survey to collect input from manufacturing companies about their current Twin Transition status and future goals.
2. A Twin Transition maturity model that compares a company's current state to its goals, based on key sustainability and digital transformation indicators.
3. A component that recommends next steps and appropriate digital technologies, taking into account both positive and negative sustainability impacts.

This phase answers **sub-research question 3**: *What is the corresponding decision-support tool that integrates the identified requirements to support Dutch high-tech manufacturing companies in implementing the Twin Transition?*

Multiple data sources and methods were used in this phase:

- Environmental, social and governance impacts were selected using a production-based Environmentally Extended Input-Output Analysis (EEIOA) and the MSCI ESG Industry Materiality Map. This ensured that the most relevant impacts, aligned with CSRD reporting standards, were in-

cluded.

- A structured review of academic and grey literature was used to link digital manufacturing technologies to these sustainability impacts.
- Based on an internal Accenture model, a tailored Twin Transition maturity model was developed. This included five maturity levels across several dimensions and sub-dimensions, which were aligned with both sustainability goals and digital technology use.
- To support decision-making, digital technologies were assessed on both their potential positive and negative sustainability impacts, as well as their implementation complexity. These insights were used to build the “next steps” module.
- A first version of the tool interface was tested in two semi-structured interviews with participants that fit the intended user profile. Their feedback was used to adjust both the content and the design of the tool.

This phase resulted in a functioning prototype that brings together data, user input, and recommendations in an integrated and user-friendly format, in line with the outlined requirements from phase 2.

2.2.4. Phases 4 and 5: Demonstration and evaluation

The final two phases, demonstration and evaluation, were combined due to time limitations. The goal was to demonstrate and test the tool with real users and gather feedback on its usability, relevance, and value. These phases answer:

- **Sub-research question 4:** *How does the integrated decision-support tool for the Dutch high-tech manufacturing sector perform when demonstrated to intended target users?*
- **Sub-research question 5:** *How can the proposed decision-support tool be improved, based on the results of the demonstration phase?*

The tool was demonstrated through semi-structured interviews with a mix of representatives from Dutch high-tech companies and consultants at Accenture Industry X. During these sessions, participants were asked to use the tool and reflect on its design and outputs. The feedback was used to assess:

- How well the tool met the needs of the target users.
- Whether the tool provided clear, useful recommendations.
- What improvements could be made to better support decision-making.

The results of this phase informed a set of final recommendations for improving the tool and suggestions for future research and development.

2.3. Overview of methods

This section outlines the data collection methods used to develop and evaluate the decision-support tool for implementing the Twin Transitions in Dutch high-tech manufacturing companies, in line with the DSR methodology. These methods are presented here because they are applied across multiple phases of the DSR process. More detailed descriptions of how each method is used are provided in the corresponding phase-specific chapters, this section serves to give a consolidated overview.

A combination of primary and secondary data was collected to ensure both practical relevance and theoretical grounding (Johannesson and Perjons, 2014, p.111). Primary data was obtained through semi-structured interviews and a supervised survey, offering first-hand insights into stakeholder experiences, current practices, and the challenges faced during Twin Transition implementation. Secondary data, drawn from academic literature and industry reports, provided a solid theoretical foundation and enabled comparative analysis, situating the research within established academic and industrial frameworks.

2.3.1. Structured literature review: PRISMA for identifying research articles

The structured literature reviews in this study follows the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) methodology for selecting papers to analyze. PRISMA provides a structured framework that ensures transparency, completeness, and reproducibility in structured reviews (Page et al., 2021).

The paper selection process follows a phased approach, beginning with the definition of key search terms and the selection of suitable databases. Subsequently, relevant records from various bibliographic databases are identified, followed by a screening phase where duplicate records and irrelevant studies are excluded. The eligibility phase then involves the assessment of articles to determine their alignment with the research focus. Finally, the inclusion phase results in the selection of studies that provide valuable insights into the goal of the literature review.

Identification To ensure comprehensiveness, the literature search is conducted using two major academic databases: Scopus and Web of Science. These databases were chosen for their extensive coverage of peer-reviewed literature across multiple disciplines. Other databases were not included, as Scopus and Web of Science already provide broad and overlapping coverage of high-quality, peer-reviewed sources relevant to the research topic, making their use both sufficient and methodologically sound for a scientifically rigorous review. While Scopus offers enriched citation analytics and broad subject coverage, Web of Science provides access to a diverse range of research outputs, including conference proceedings and book reviews (Elsevier, 2025; Clarivate, 2025). The combination of both databases ensures that no relevant research is overlooked, thereby strengthening the robustness of the structured review (Wageningen University & Research, 2025).

In addition, for some of the structured reviews, forward snowballing was also applied to identify further relevant studies that may not have appeared in the initial database search. Here, Google Scholar was used to discover more recent research that builds on the articles that were already identified.

Screening The screening phase is designed to refine the search results. Predefined criteria were applied to titles, abstracts, and keywords. These criteria ensured that only relevant papers would be processed at a later stage in the research.

Eligibility Following the screening phase, the eligibility assessment further refines the selection of studies by applying more specific content-related criteria. These criteria were established in line with the sub-research question or goal of the literature review. The eligibility phase consisted of two rounds. First, content-related criteria were applied to the titles, abstracts and keywords of papers. A second round of eligibility assessment was conducted to refine the number of papers selected based on the full text using the same content-related criteria.

Included The final phase determined which papers would be included in the structured review. Figure 2.1 shows an overview how all four phases in the PRISMA method for identifying relevant research articles are connected.

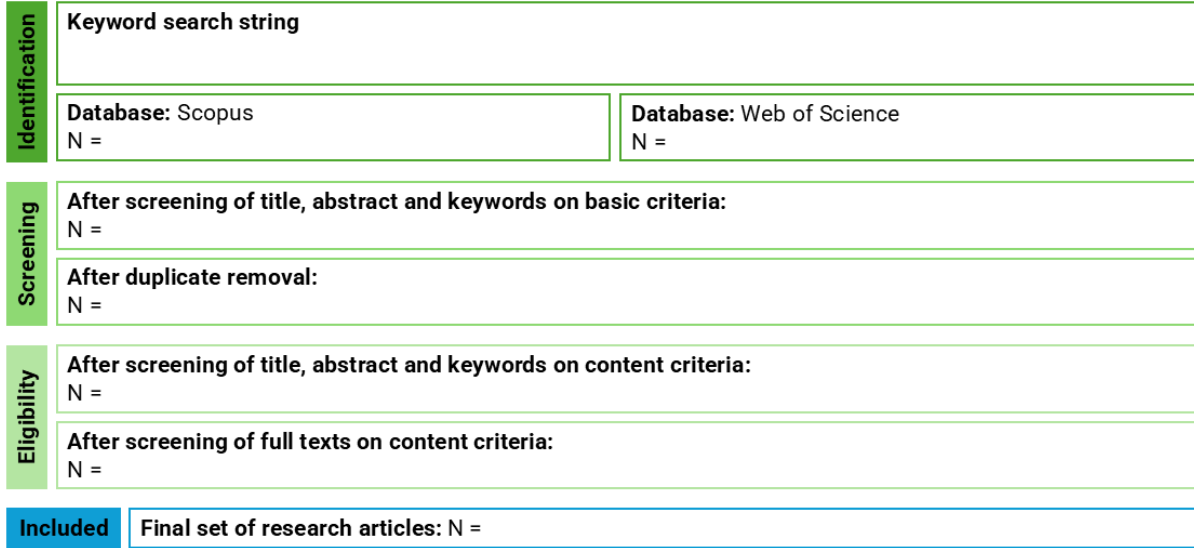


Figure 2.1: Flow for identification of relevant research papers following the PRISMA methodology, consisting of four different stages.

2.3.2. Semi-structured interviews

This research used semi-structured interviews across several phases to explore, test, and develop insights about how the Twin Transitions are being implemented in the Dutch high-tech manufacturing sector. The interviews were essential for linking findings from the literature to real-world experiences and helped shape the design of a practical decision-support tool. This section explains how the interviews were prepared, carried out, and analyzed.

Interview preparation

Ethical conduct Ethical research practice was maintained throughout all interview phases. Prior to participation, all respondents received a written explanation outlining the research purpose, interview format, confidentiality protocols, and their rights, including the option to decline questions or withdraw from the study without consequence. Participants were asked to provide informed consent via email or in writing before interviews were scheduled. Explicit permission was sought and obtained for audio recording of each session.

This approach followed the ethical code of conduct established by TU Delft. The guidelines require informed consent, protection of participant anonymity, and secure data handling. The research received formal approval from the TU Delft Human Research Ethics Committee (HREC), confirming its compliance with all relevant ethical standards (ID: 5265).

Participant selection A purposive sampling strategy was used in all three phases to select participants with relevant expertise, given the research focus and time constraints.

In Phase 1, participants were drawn from academia, industry, and related institutions to provide a broad view of the Dutch high-tech manufacturing sector. All had strong experience with digital transformation, though not necessarily in sustainability. This selection is based on the assumption that participants with strong expertise in digital transformation, but less experience in sustainability, could provide realistic and practical insights into how sustainability goals may be integrated into existing digital initiatives. Eight participants were recruited through direct outreach and referrals via academic and internship networks.

In Phase 2, the goal was to engage users who closely matched the intended profile for the decision-support tool. Five consultants from Accenture were interviewed, selected for their varied experience across high-tech sub-sectors and roles. In Phase 3, two participants were selected for their hands-on experience with strategy implementation, allowing for detailed feedback on the tool prototype and technology–sustainability links. Both were identified through referrals from Phase 2 and also worked at Accenture.

Pre-interview communication In the first two phases of the research, participants were also asked to complete a short online survey prior to the interview. In Phase 1, this survey focused on ranking 13 Twin Transition challenges identified through a literature review. These rankings helped tailor the interviews to each participant's expertise and priorities. In Phase 2, the survey asked participants to review and prioritize a set of proposed functional, structural, and contextual requirements for the decision-support tool. This helped direct the conversation toward topics of greatest relevance. The survey responses were not treated in isolation; they were integrated into the interview scripts and later combined with the qualitative data to enrich the analysis. In Phase 3, participants were also sent a short document in advance that outlined how different digital technologies relate to sustainability goals, including potential trade-offs. This helped introduce them to the themes that would come up during the demonstration of the tool.

Across all phases, the surveys and preparation materials were provided with the intention of helping participants become familiar with the core topics and structure of the interview, without revealing the exact questions in advance. This approach allowed participants to reflect on the issues ahead of time and arrive well-prepared, while still encouraging spontaneous and authentic responses during the actual conversation.

Interview data collection

All interviews were conducted one-on-one, which allowed for open, in-depth discussions. Depending on location and availability, the interviews were held either in person or via Microsoft Teams. This flexible setup made it easier to include a broad range of participants from academia, industry, consulting

and umbrella organizations. Each phase followed a semi-structured interview format, meaning the interviewer used a consistent set of guiding questions while leaving space to follow up on new ideas or clarify points raised by the interviewee. This flexible approach made it possible to adapt the conversation based on the specific expertise or interests of each participant.

The interviews were tailored to the goals of each research phase. In Phase 1, questions focused on how the challenges identified in the literature were experienced in practice, and whether any key issues were missing. In Phase 2, the discussion shifted toward gathering feedback on the literature identified functional, structural and contextual requirements for design and development of the decision-support tool. In Phase 3, interviewees were presented with a prototype of the tool. They were first walked through the prototype during the session and then given an overview of the digital–sustainability linkages to review on their own during the session. The conversation centered on their experience using the tool, including how clear and useful they found it, and what improvements they would suggest.

Interview data processing

To ensure accuracy and allow for detailed analysis, all interviews were recorded with the participant's consent and transcribed via Teams. Transcripts were reviewed closely manually, both for familiarization and for identifying recurring themes and meaningful differences across responses. All identifying information was anonymized in the final transcripts.

The analysis of interview data varied slightly across the three phases, each aligned with the specific goal of that phase.

Phase 1 In this phase, the goal was to refine and tailor the 13 literature-based challenges to the Dutch high-tech manufacturing context. A structured codebook was developed to guide the analysis, categorizing interview input as additions, specifications, contrasts, or examples. This ensured a consistent link between the interview data and the original challenge definitions. The analysis was conducted in two stages using Microsoft Excel. First, transcripts were coded per interviewee, with key insights translated where needed and summarized alongside illustrative quotes. In the second stage, data was reorganized by challenge, allowing all related input to be compared with the literature definitions. Where differences emerged, the interview findings were prioritized, ensuring that the final challenge definitions reflected both theoretical grounding and sector-specific experience.

Phase 2 In this phase, the interview analysis focused on refining and prioritizing the functional, structural, and contextual requirements for the decision-support tool. These requirements were initially derived from three sources: the Twin Transition challenges identified in Phase 1 (functional requirements), insights from the literature (structural requirements), and the intended user profile (contextual requirements). The aim was to use participants' feedback to validate these requirements, assess their relevance, and incorporate any additional suggestions to better align the tool with user needs. A structured thematic analysis was conducted in ATLAS.ti, following three coding stages: open, axial, and selective coding. During the open coding stage, descriptive codes were assigned to short excerpts from the transcripts to capture key ideas, with multiple codes often applied to a single excerpt to reflect overlapping insights. In the axial coding stage, these codes were organized into broader categories to reveal patterns across interviews, grouped according to the three requirement types. Through constant comparison, these categories were refined to highlight more specific themes, for example, distinguishing internal benchmarking needs from peer benchmarking. Finally, in the selective coding stage, the most relevant and frequently mentioned themes were identified and translated into concrete, prioritized requirement definitions for the tool.

Phase 3 In this phase, the interview analysis of the first iteration of the decision-support tool (hereafter referred to as design cycle 1) aimed to assess whether the functional, structural, and contextual requirements defined in Phase 2 were effectively reflected in the intermediate tool design. In addition, it aimed to confirm or expand the links between digital manufacturing technologies and their sustainability impacts, as defined by the ESRS framework. The analysis followed the same thematic coding approach used in Phase 2. Interview transcripts were reviewed to identify feedback related to both the design and usability of the tool, as well as comments on the alignment between specific digital technologies and ESRS-related sustainability dimensions. The coded insights were then grouped and compared with the original requirements and literature-based connections.

Across all three phases, each interview was summarized after analysis and shared with the respective participant for review. This validation step allowed interviewees to confirm the accuracy of their contributions and clarify any points if needed. In only a few cases, minor changes were requested to improve clarity or nuance. Overall, participants confirmed the summaries, supporting the reliability and transparency of the findings.

2.3.3. EEIOA for quantifying environmental impacts

To assess the relevance of environmental impacts under the ESRS, Environmentally Extended Input-Output Analysis (EEIOA) was used. This method is well-suited for evaluating sector-wide environmental effects at a national level. By applying EEIOA to the Dutch high-tech manufacturing sector, it becomes possible to determine which ESRS environmental indicators are significant in terms of actual impact. For example, if a pollutant is listed in the ESRS, EEIOA helps assess whether this sector contributes to it in meaningful quantities or only minimally. This ensures that the final decision-support tool focuses on the most material and relevant environmental indicators.

EEIOA is a method used to quantify the environmental impacts of economic activities at the level of entire economies or specific sectors (Miller and Blair, 2009). In basic IOA, the economic structure of an economy is mapped by recording the flows of goods and services between industries. The output of one industry serves as the input to another, forming an interconnected web of economic activity. By adding environmental extensions to this framework, EEIOA enables the quantification of environmental impacts, such as emissions, resource use, and energy consumption, associated with each economic transaction. This provides a holistic view of how economic production and consumption contribute to environmental impact. While EEIOA can be applied to assess impacts across complete supply chains, in this research it is specifically used to measure the direct environmental impacts of production activities from the Dutch high-tech manufacturing sector. This focus on production aligns with the scope of the study and makes EEIOA an appropriate method for providing a sector-wide estimate of these impacts.

2.3.4. The database used

For this study, the EXIOBASE 3 database was selected. EXIOBASE 3 is a globally recognized Environmentally Extended Multi-Regional Input-Output (EE-MRIO) database. It offers high sectoral detail, with 163 industries and 200 products distinguished, and covers a wide array of environmental and social indicators. This makes it particularly well suited for detailed sectoral-level sustainability analyses.

Key environmental indicators available in EXIOBASE 3 that are in line with the CSRD relevant for the high-tech manufacturing sector include:

- Air emissions (e.g., CO₂, CH₄, NO_x, SO₂),
- Energy use (e.g., electricity, fossil fuels, renewables),
- Water use (e.g., blue water, green water),
- Material extraction and use,
- Employment numbers.

Each environmental and social flow is linked to specific sectors and countries or regions. The multi-regional nature of EXIOBASE allows for both global supply chain tracing and regional isolation, which is key for this study focused on the Dutch high-tech manufacturing sector.

EXIOBASE provides the necessary matrices for EEIOA calculations, including:

- The technical coefficients matrix (A),
- The final demand matrix (Y),
- Environmental extensions matrices (F for sectoral emissions, F_{hh} for household emissions).

2.3.5. Application to this study

Definition of the Dutch high-tech manufacturing sector

While EXIOBASE 3 offers a high level of sectoral detail, it does not contain a single sector that exactly corresponds to the Dutch high-tech manufacturing sector as it is defined in national or policy contexts. Consequently, it was necessary to approximate and construct the Dutch high-tech manufacturing sector within the available EXIOBASE structure.

Since EXIOBASE is fundamentally an economic model, built around supply-use tables and input–output flows, it was logical to also define the Dutch high-tech manufacturing sector based on economic criteria. This approach ensures consistency between the way sectors are delineated in the database and the way the sector was defined for the purpose of this analysis.

To do this, the sector definition developed by Velthuisen et al. (2024) was used. In that report, the Dutch high-tech manufacturing sector is characterized by combining parts of several standard manufacturing sectors. The definition relies on the contribution of each sub-sector to the Dutch GDP. This indicator is appropriate because it captures the economic contribution of the high-tech manufacturing sector, aligning with the calculation method of EEIOA.

Using this definition, specific manufacturing sectors within EXIOBASE were selected that align closely with the high-tech activities identified in the Velthuisen et al. (2024) report. These sectors included:

- Manufacture of office machinery and computers,
- Manufacture of electrical machinery and apparatus,
- Manufacture of radio, television, and communication equipment,
- Manufacture of medical, precision, and optical instruments,
- Manufacture of motor vehicles, trailers, and semi-trailers,
- Manufacture of other transport equipment,
- Chemicals not elsewhere classified,
- Manufacture of rubber and plastic products (used as a proxy for pharmaceutical production).

Each of these sectors was assigned a weight based on its proportional contribution to the Dutch high-tech manufacturing sector, derived from its GDP share according to the Velthuisen et al. (2024) report. These GDP-based weights were then normalized so that there was one definition of the Dutch high-tech manufacturing sector based on the parts of other sub sectors. These weights were used to proportionally allocate environmental impacts (e.g., emissions, energy use) from the broader EXIOBASE manufacturing sectors to the constructed Dutch high-tech manufacturing sector.

This weighted aggregation method ensures that the constructed Dutch high-tech manufacturing sector in EXIOBASE reflects the economic significance of the real-world Dutch high-tech manufacturing sector. It allows for a more accurate and meaningful sustainability impact analysis at the level of the sector of interest, despite the lack of a perfect one-to-one sector match in the source database.

EEIOA accounting approach

The main methodological approach in this study is production-based accounting (PBA). This decision was based on the objective of the research: to assess the direct environmental impacts generated within the Dutch high-tech manufacturing sector itself.

Production-based accounting attributes impacts to the location where the production activity occurs, irrespective of where the products are consumed. In contrast, consumption-based accounting (CBA) attributes impacts to the final consumers, tracing impacts through international supply chains. Since this study focuses on sustainability improvements for the manufacturing operations of Dutch high-tech manufacturers, PBA was the appropriate framework.

To ensure robustness, the sustainability impacts of the Dutch high-tech manufacturing sector were calculated over the time period from 2012 to 2022. This period was carefully selected to ensure that the results would not be biased by unusual short-term economic or production disruptions. A key consideration for choosing this time frame was the occurrence of the COVID-19 pandemic starting in 2020. COVID-19 had a significant impact on global supply chains, production levels, and economic activity. Many manufacturing sectors, including high-tech manufacturing, experienced reductions or shifts in production volumes during 2020 and 2021. If only a single year had been analyzed, the results might have been strongly affected by these exceptional circumstances, leading to misleading conclusions.

In practical terms, the availability of EXIOBASE 3 data also influenced the choice of years. At the time of this research, EXIOBASE 3 contained complete environmental and economic data up to 2022. For the energy-related environmental extensions specifically, data was only available up to 2020. The following subsections describe the detailed calculation steps.

Calculation of the Leontief inverse

The first step involved calculating the Leontief inverse matrix (L). The technical coefficients matrix A

describes how much input from each sector is needed to produce one unit of output in another sector. The Leontief inverse is given by:

$$\mathbf{L} = (\mathbf{I} - \mathbf{A})^{-1}$$

where $\mathbf{I}$ is the identity matrix.

The Leontief inverse captures both the direct and indirect input requirements needed to satisfy a unit of final demand. It accounts for the cascading effects of inter-sectoral dependencies in the economy.

Calculation of total sector outputs

Using the Leontief inverse, the total sectoral outputs $\mathbf{x}$ were computed. This involved summing the final demand matrix $\mathbf{Y}$ across all final demand categories to obtain $\mathbf{Y}_{\text{sum}}$, and then:

$$\mathbf{x} = \mathbf{L} \times \mathbf{Y}_{\text{sum}}$$

This calculation determines the total economic output of each sector needed to meet observed final demands, incorporating all upstream production requirements.

Calculation of emission intensities

Next, the environmental extension matrices $\mathbf{F}_{\text{air}}$ were used to determine sectoral emission intensities. For each gas g (e.g., CO_2 , CH_4 , NO_x), the intensity vector $\mathbf{f}_g$ was calculated as:

$$\mathbf{f}_g = \mathbf{F}_{\text{air},g} \times \text{diag}(\mathbf{x})^{-1}$$

This gives emissions per unit of output for each sector, normalizing the raw emissions data by the scale of sectoral production.

Calculation of Direct Production-Based Emissions

Direct, production-based emissions $\mathbf{e}_g$ were calculated by applying the emission intensities to actual sectoral outputs:

$$\mathbf{e}_g = \text{diag}(\mathbf{f}_g) \times \mathbf{x}$$

The emissions were reshaped into a (region $\times$ sector) format, enabling the extraction of emissions specifically associated with the Netherlands.

Selection of Dutch high-tech manufacturing emissions

Dutch emissions related to the Dutch high-tech manufacturing sector were selected by identifying relevant Dutch sectors and applying GDP-share weights. The total Dutch high-tech manufacturing emissions for each gas were calculated as:

$$\text{Emissions}_{\text{Dutch high-tech manufacturing}} = \sum_i w_i \times \text{Emissions}_i$$

where w_i represents the normalized GDP weight of sector i .

Conversion to CO₂-equivalents

Greenhouse gas emissions were converted into CO₂-equivalent units to allow aggregation across gases. This was done by applying global warming potentials (GWP) from IPCC AR6 for each gas (Intergovernmental Panel on Climate Change (IPCC), 2024):

$$\text{Emissions}_{\text{CO}_2\text{-eq}} = \text{Emissions}_g \times \text{GWP}_g$$

This step ensures comparability across gases with different climate impacts.

Comparison with Consumption-Based Accounting (CBA)

Although the focus was on production-based impacts, supply chain (CBA) impacts were also calculated for comparison. First, the direct outputs of the Dutch high-tech manufacturing sectors ($\mathbf{x}_{\text{Dutch high-tech manufacturing}}$)

were isolated. Then, using the Leontief inverse, total upstream production requirements were calculated:

$$\mathbf{x}_{\text{upstream}} = \mathbf{L} \times \mathbf{x}_{\text{Dutch high-tech manufacturing}}$$

Subsequently, supply-chain emissions were calculated:

$$\text{Emissions}_{\text{upstream},g} = \mathbf{f}_g \times \mathbf{x}_{\text{upstream}}$$

Finally, the ratio of direct to upstream emissions was computed:

$$\text{Ratio} = \frac{\text{Direct emissions}}{\text{Upstream emissions}}$$

This ratio provides insights into whether environmental impacts are mainly generated within the sector itself or embedded in upstream supply chains.

All Python code for the EEIOA can be found via this GitHub link: <https://github.com/MIdeGier/Thesis-EEIOA.git>.

2.3.6. Supervised survey evaluation

The evaluation of the decision-support tool in Phase 4 employed a supervised survey interview format, combining structured assessment with in-depth qualitative feedback. This method was designed to systematically evaluate how well the developed tool met the established requirements while capturing detailed insights into user experience and potential improvements. The supervised approach ensured comprehensive evaluation by guiding participants through both tool demonstration and structured requirement assessment.

Survey preparation

Ethical conduct The supervised survey interviews followed the same ethical protocols established for the semi-structured interviews described in Section 2.3.2. All participants received written information about the research purpose, interview format, and their rights, including the option to decline participation or withdraw at any time. Informed consent was obtained prior to scheduling, and explicit permission was secured for audio recording. The research maintained compliance with TU Delft's ethical code of conduct and HREC approval (ID: 5265).

Participant selection A purposive sampling strategy was employed to select participants who closely matched the intended user profile for the decision-support tool. The selection prioritized diversity in professional backgrounds to ensure comprehensive evaluation across both strategic and operational aspects. Five participants were recruited, representing expertise in manufacturing technology implementation, sustainability strategy, and ESG performance. Three participants were consultants from Accenture with varying specializations in high-tech sectors, while two participants represented the company perspective from a Dutch manufacturing organization. This combination ensured evaluation from both consultancy and industry viewpoints, reflecting the tool's intended dual audience.

Pre-interview communication Due to varying participant availability, the preparation format was adapted accordingly. Two participants with greater time availability received the evaluation survey in advance and completed it prior to the interview session. The remaining participants with more limited availability were guided through the survey during the interview itself. All participants received background materials explaining the tool's purpose and the evaluation framework, allowing them to familiarize themselves with the assessment context without compromising the authenticity of their responses.

Survey data collection

The supervised survey interviews combined live demonstration with structured assessment, creating a comprehensive evaluation experience. Each session began with a systematic walkthrough of the web-based tool, during which the researcher demonstrated different sections including the maturity model interface and next-step recommendation system. The demonstration was tailored to each participant's

expertise, using familiar technologies to validate the tool's framing while introducing less familiar concepts to test communication clarity.

Following the demonstration, a split-screen setup was employed with the tool displayed on one side and the requirement list on the other. This visual arrangement facilitated informed assessment, as participants could reference specific tool features while evaluating each requirement. For each of the functional, structural, and contextual requirements established in Phase 2, participants were asked to rate the tool's performance using a three-point scale: 'not fulfilled', 'partially fulfilled', or 'fully fulfilled'. The structured discussion format enabled in-depth follow-up questions to understand participants' reasoning and gather specific examples. The full interview protocol can be found in Appendix E.1.1.

The supervised format provided several advantages over independent survey completion. The guided approach ensured participants had comprehensive understanding of all tool features before assessment, leading to more informed evaluations. The interactive nature enabled immediate clarification of questions and deeper exploration of participants' reasoning through follow-up discussions. Additionally, the real-time format allowed for dynamic adaptation based on participant expertise and interests.

However, this approach also introduced potential limitations. The presence of the researcher during evaluation may have created social desirability bias, with participants potentially reluctant to provide negative feedback directly. The guided demonstration could also have influenced participants' perceptions of the tool's capabilities. These trade-offs were considered acceptable given the richer insights obtained through the interactive format and the opportunity for immediate clarification and deeper understanding.

Data processing

All supervised survey interviews were audio recorded with participant consent and transcribed using Microsoft Teams. The analysis followed the same thematic coding methodology employed in Phase 2, using ATLAS.ti software for systematic data processing. The approach consisted of three sequential coding phases: open, axial, and selective coding. During open coding, descriptive codes were assigned to meaningful excerpts from interview transcripts, capturing both quantitative ratings and qualitative reasoning behind assessments. The axial coding phase grouped related codes into broader themes aligned with the three requirement categories (functional, structural, and contextual). Constant comparison was employed throughout this process, ensuring newly coded content was continuously reviewed against existing categories for internal consistency. The selective coding phase identified the most relevant and recurring themes, focusing on insights critical for evaluating requirement fulfillment and identifying improvement opportunities.

To strengthen the reliability and validity of the analysis, following the completion of coding, individual summaries of key findings were prepared for each participant (see Appendix E.1.2). The summaries were then shared with respective participants for feedback and validation, allowing them to confirm interpretation accuracy and provide clarification where needed.

The analysis was specifically structured to align with the requirement evaluation framework established in Phase 2. Coded insights were systematically mapped against each functional, structural, and contextual requirement, enabling comprehensive assessment of the tool's performance across all defined criteria. This structured approach facilitated identification of both well-fulfilled requirements and areas requiring improvement, supporting the dual research objectives of performance evaluation and enhancement identification.

2.4. Summary of the research approach

Figure 2.2 shows how the five DSR phases are linked to the sub-research questions, which methods were used to answer each question, and what outputs were generated in each phase. These outputs then inform the sub-research question of the following phase, creating a clear step-by-step connection throughout the research process.

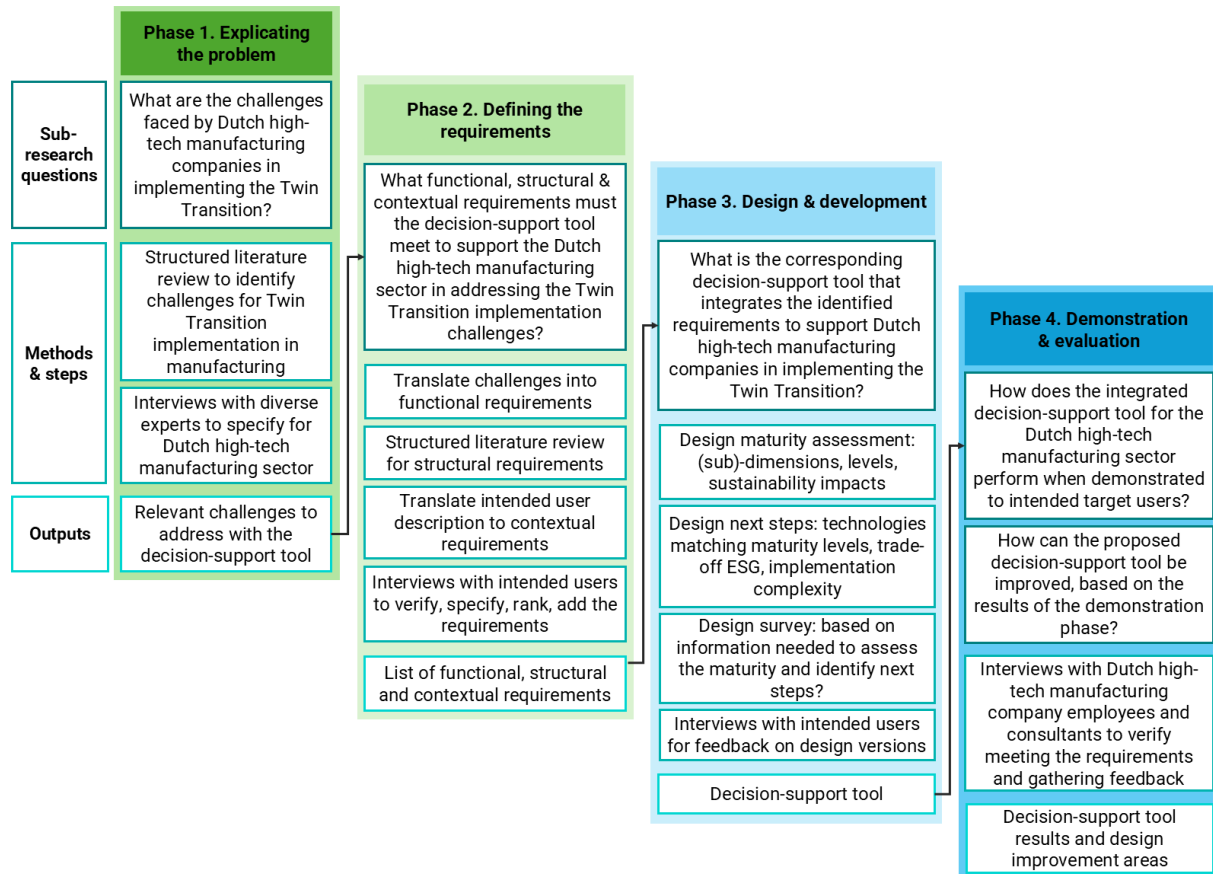


Figure 2.2: Research approach based on the five DSR phases and their corresponding sub-research questions in line with the methods and outputs of each phase.

3

Phase 1: Explicating the problem

This chapter identifies and analyzes the practical challenges faced by Dutch high-tech manufacturing companies in implementing the Twin Transition. The integration of digital technologies to address sustainability challenges is complex, and understanding this interaction is important. Therefore, this phase of the research addresses **sub-research question 1**: *“What are the challenges faced by Dutch high-tech manufacturing companies in implementing the Twin Transition?”*

To address this question, a structured literature review is conducted to identify the challenges involved in implementing the Twin Transition in the general manufacturing sector. These findings provide the foundation for specifying how these challenges apply to the Dutch high-tech manufacturing sector. This is done through interviews with experts from diverse backgrounds. The results of these methods formulate a clear and well-justified problem statement, highlighting the need for an integrated decision-support tool. Furthermore, identify the specific challenges that such a tool should address to support Dutch high-tech manufacturing companies in effectively implementing the Twin Transition.

3.1. Literature review

A structured review is conducted to identify the challenges experienced by the manufacturing sector in advancing the Twin Transition. This approach is suitable because it allows for a structured, comprehensive, and unbiased assessment of existing literature, ensuring that the full spectrum of challenges is captured (Webster and Watson, 2002). Given that the Twin Transition is a relatively new concept, a broad exploration of academic sources is necessary to map out the challenges faced by the sector.

At this stage of the study, the focus remains on the manufacturing sector as a whole, rather than specifically focusing on the Dutch high-tech manufacturing sector. At the time of the research, no relevant academic literature was found in the reviewed scientific databases that directly addressed the high-tech manufacturing sector (resulting in no matches whatsoever), let alone literature focused on the Dutch context. Therefore, broadening the scope to the general manufacturing sector allows for the identification of a comprehensive set of challenges and insights, which can later be adapted and applied to the specific context of Dutch high-tech manufacturing.

3.1.1. Structured review methodology for identifying relevant research articles

This structured literature review follows the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) methodology as described in Section 2.3.1. Figure 3.1 details how the four steps are applied to identify suitable articles for identification of Twin Transition implementation challenges for the manufacturing sector. Appendix B.1.1 gives a more in depth description of how each step was done following the PRISMA methodology specifically for this literature review. A detailed overview of the included papers is provided in Appendix B.1, Table B.2.

Identification	Keyword search string: ("twin transition" OR "twin transformation" OR "dual transition" OR "dual transformation" OR "green-digital nexus" OR "green-digital transition" OR "green-digital transformation") AND (manufactur* OR production OR industrial*)	
	Database: Scopus N = 174	Database: Web of Science N = 745
Screening	After screening of title, abstract and keywords on basic criteria (accessible, English, between 2020-2025): N = 844	
	After duplicate removal: N = 483	
Eligibility	After screening of title, abstract and keywords on content criteria (twin transition, manufacturing, socio-technical): N = 37	
	After screening of full texts on content criteria (twin transition, manufacturing, socio-technical): N = 34	
Included	Final set of research articles: N = 34	

Figure 3.1: Identification of relevant research papers following the PRISMA methodology, consisting of four different stages.

3.1.2. Results: Twin Transition implementation challenges according to literature

Based on the reviewed literature, thirteen key challenges have been identified that affect the implementation of the Twin Transition in the manufacturing sector. The detailed interpretations and perspectives of each author are presented individually in Appendix B.1, Table B.3. In this section, these individual insights are synthesized and organized into thirteen overarching challenges. The full description of all the challenges according to the combined insights from various authors, can be found in Section B.1.4 in Appendix B.1.

The thirteen challenges identified through literature are (the order in which these challenges are listed does not imply any hierarchy or relative importance):

1. **The high implementation costs of both the digital and sustainability aspects of the Twin Transition present a significant barrier.** Pursuing both digital transformation and sustainability requires substantial investment in technology, infrastructure, workforce development, and energy-efficient systems. Many businesses view the green transition as financially demanding, and the added complexity of integrating it with digital initiatives intensifies cost pressures. This dual investment can strain financial resources and lead to delays in implementation.
2. **There is a lack of understanding in what the economic returns will be when implementing measures for the Twin Transition.** Uncertainty about the economic benefits of digital transformation often leads to hesitation among businesses. This stems from delayed returns, the immaturity of some technologies, and limited understanding of their value. The difficulty in quantifying return on investment, especially for digital and sustainable solutions, adds to the risk, making it harder for companies to justify and confidently commit to these investments.
3. **The sustainability impact of digital technologies remains poorly understood by manufacturing companies.** Manufacturing companies often face difficulty evaluating whether digital technologies align with sustainability goals. Although these solutions can enhance efficiency, their environmental impact is not well understood. This knowledge gap hinders adoption and limits the realization of potential sustainability benefits.
4. **There is a shortage of clear, practice-based examples of transition pathways for the Twin Transition.** Although the European Union promotes the Twin Transition through frameworks like the Digital Economy and Society Index (DESI), the lack of sector-specific best practices creates uncertainty. Without clear examples, companies struggle to select appropriate strategies, technologies, and investment levels. This scarcity of real-world use cases limits guidance and hinders practical implementation.
5. **Manufacturing companies lack tailored strategies that address their unique starting points in**

- each of the Twin Transition.** The lack of tailored methodologies for Twin Transition strategies often hinders effective implementation. Most existing assessment tools are too generic, overlooking key factors such as company size, production type, and specific operational needs
6. **The evolving nature of the Twin Transition adds complexity to their implementation for manufacturing companies.** The Twin Transition takes place in constantly changing landscapes. Both new digital technologies emerge and sustainability impacts shift across supply chains, so companies face a dynamic and often uncertain environment. This ongoing change, driven by technological advances and evolving customer needs, makes implementation challenging and frequently leads to delays.
 7. **Unquantified decisions within the Twin Transition complicate long-term decision-making.** One of the key challenges in the Twin Transition is the lack of quantification in decision-making, which hinders long-term strategic planning. Clear, standardized metrics are important to reduce uncertainty, yet many manufacturing companies lack the evaluation criteria needed to assess Twin Transition efforts. Without reliable data, firms struggle to make informed investment decisions, often resulting in delayed progress.
 8. **The Twin Transition demands new skills from both the company and its employees.** The Twin Transition requires companies and their employees to develop new skills in areas such as digital technologies, sustainability, resilience, and organizational management. As inherently multi- and interdisciplinary processes, they call for collaboration across departments rather than relying solely on top management. However, gaps in knowledge or competence, whether in implementing digital solutions or advancing sustainability, can significantly hinder progress.
 9. **Resistance from employees may arise due to the extensive changes required by the Twin Transition.** Digital transformation brings continuous change, often creating tension between established practices and emerging technologies. Industry 4.0 can reshape employment dynamics, introducing pressures such as constant availability, new performance metrics, and less regulated work relationships. Employees may resist these changes due to concerns about retraining, unfamiliar digital tools, or job security, especially as automation replaces certain tasks and demands adaptation to both digital and sustainability transitions.
 10. **The Twin Transition may necessitate organizational restructuring, such as increased collaboration.** A successful Twin Transition requires companies to rethink their role in the value chain and how they create value. This involves aligning technological and managerial transformations while supporting cross-functional collaboration. Implementation often demands closer coordination across departments, leading to shifts in organizational structures and the emergence of new roles.
 11. **There is insufficient focus on social sustainability within the Twin Transition, as the link between environmental sustainability and digitalization is clearer.** Companies often emphasize economic and environmental goals while overlooking social sustainability, especially when digital transformation drives the agenda. This can create a disconnect between ecological progress and fair working conditions. The Twin Transition requires not only technical and managerial expertise but also attention to social dimensions.
 12. **Navigating the dual and evolving regulations governing the Twin Transition presents an added challenge.** Companies must keep pace with evolving regulations to remain compliant, but ongoing policy development creates uncertainty. Shifting standards, carbon pricing, and compliance rules make it difficult to align strategies without risking non-compliance or added costs. As a result, many manufacturers delay investing in climate-friendly technologies, waiting for clearer regulatory guidance.
 13. **Managing regulations related to the Twin Transition domains while remaining competitive is difficult.** Manufacturing companies face the challenge of meeting environmental regulations while remaining competitive. Balancing compliance with the demands of the Twin Transition and maintaining a competitive edge is a difficulty for many firms.

3.2. Interviews

Section 3.1 identified 13 challenges from the literature for the manufacturing sector in general when implementing the Twin Transition. To tailor these challenges to the specific context of the Dutch high-tech manufacturing sector, a qualitative approach was employed through expert interviews. This method

provided a way to explore the literature-based findings in greater depth and relevance.

Interviews were chosen instead of surveys because this research is semi-exploratory. The specifics of the challenges, as perceived by stakeholders in the Dutch high-tech manufacturing sector, was not known beforehand. Surveys often limit responses to predefined options and lack the flexibility to explore unexpected insights. In contrast, in-depth interviews allow for open-ended dialogue, enabling the researcher to probe for clarification and examples. This makes interviews particularly suitable for capturing the detailed and nuanced perspectives necessary to identify the specifics for the Dutch high-tech manufacturing sector.

3.2.1. Interview design

Format: semi-structured interviews

The interviews in this phase followed the semi-structured methodology described in Section 2.3.2, with adaptations tailored to the refinement of literature-defined Twin Transition challenges in the Dutch high-tech manufacturing sector. Each interview was guided by a protocol prepared in advance, containing general guidelines for ethical conduct, a set of guiding questions, and personalized structure based on pre-interview input from participants.

Prior to each interview, participants were asked to complete a short survey ranking the perceived importance of 13 implementation challenges over two time horizons: the next five years and the following five to ten years. This ranking helped determine the discussion order of challenges during the interview, allowing the conversation to begin with the most relevant challenges for the interviewee. The complete survey and an example protocol are available in Appendix B.2.

The interviews were designed to last approximately one hour and followed a flexible structure. While guided by a predefined set of topics, the semi-structured format allowed for open-ended responses and spontaneous elaboration. This ensured a balance between comparability across interviews and the depth and authenticity of participant input. Interviews were primarily conducted in Dutch to support more fluent and precise expression, as Dutch was the native language of most interviewees. Visual aids, including the participant's pre-ranked challenges, were shared during the interview to prevent misunderstandings and enhance clarity.

Each interview followed a three-part sequence. First, general background questions were posed, including reflections on the ranking exercise. Second, the discussion focused on the specific challenges, with participants elaborating on their relevance, manifestation, and sector-specific characteristics. Third, a brief wrap-up section encouraged open reflection, allowing participants to raise any issues not previously discussed.

Participant selection

To gain a well-rounded view of the sector, participants were chosen from diverse professional backgrounds, including academia, industry, and other relevant institutions. Table 3.1 provides an anonymized overview of the participants. From this overview, it can be concluded that the participants represented a broad spectrum of roles and possessed significant experience in both digital transformation and sustainability domains.

A purposive sampling strategy was employed to identify individuals with relevant expertise. This method involves intentionally selecting participants who can provide detailed and relevant insights into the topic of interest (Robinson, 2024). It was particularly suitable given the time constraints of the research.

Importantly, participants did not need to be sustainability experts. However, they were expected to be well-informed about digital transformation and have a strong connection to the Dutch high-tech manufacturing sector. Since digital transformation is recognized as the more mature and better understood component of the Twin Transition in this sector (van Kappen et al., 2023), participants were expected to have solid knowledge and experience in this domain. This ensured that discussions captured realistic, sector-specific challenges for integrating sustainability into ongoing digital initiatives, providing practical insights.

Participants were recruited through direct outreach or via introductions facilitated by university supervisors or internship contacts. A total of eight interviews were conducted in this phase.

Table 3.1: Anonymized overview of interview participants. Role descriptions are based on participants' self-introductions during the interviews and were validated by each interviewee. Self-assessed levels of digital transformation and sustainability knowledge were provided in the pre-interview survey.

Domain	Identifier	Anonymized description	Self-assessed level of digital transformation knowledge	Self-assessed level of sustainability knowledge
Academia	A1	Academic researcher in information systems at a technical university. 13 years of experience.	Moderately knowledgeable	Moderately knowledgeable
Academia	A2	Academic expert in digital innovation and sustainability at a business school. 22 years of experience.	Extremely knowledgeable	Moderately knowledgeable
Practice	P1	Industry professional leading client engagements in the high-tech sector, with a focus on digital transformation. More than 10 years of experience in the high-tech domain.	Very knowledgeable	Very knowledgeable
Practice	P2	Industry professional with expertise in technology and strategic consulting for the high-tech sector. 22 years of experience in the advanced technology domain.	Very knowledgeable	Moderately knowledgeable
Practice	P3	Industry professional with a background in sustainability, operations, and digital strategy, focused on tech-intensive industries. 18 years of experience in sustainability domain.	Moderately knowledgeable	Moderately knowledgeable
Miscellaneous institutes	M1	Sector lead in smart industry at a national research organization. 3 years of experience in current role, 16 years of industry experience.	Extremely knowledgeable	Extremely knowledgeable
Miscellaneous institutes	M2	Program leader working on digital innovation in manufacturing at a public research institution. 22 years of experience.	Very knowledgeable	Very knowledgeable
Miscellaneous institutes	M3	Experienced executive in the high-tech industry, now in a leadership position at a national industry association. More than 20 years of experience.	Moderately knowledgeable	Moderately knowledgeable

Data collection

This step involved conducting the interviews, transcribing them, and initiating the coding process. All interviews were held via Microsoft Teams to maintain a private and consistent setting. Each session was one-on-one between the participant and the researcher. The interviews took place between March 17th and March 24th, 2025. They each lasted approximately one hour. The interviews were recorded, and automatic transcriptions were generated by Microsoft Teams. These transcriptions required extensive manual revision to correct for errors, particularly the sections involving sector-specific terminology. This process also served as an initial engagement with the data prior to formal analysis.

3.2.2. Data processing

The primary aim of the interview analysis was to refine and contextualize the 13 challenges identified in the literature, ensuring their relevance to the Dutch high-tech manufacturing sector. To guide this process, a codebook was developed that enabled a structured interpretation of the interview data in relation to the literature-based descriptions of the Twin Transition implementation challenges in the manufacturing sector in general. The full codebook, including definitions and inclusion criteria, is presented in Table 3.2.

The analysis followed a two-stage approach. In the first stage, the codebook was applied to the interview transcripts. Relevant insights were identified, and where necessary, translated from Dutch into English. Each coded excerpt was grouped by interviewee and summarized, with representative quotes included. These summaries were then returned to participants for feedback. This step helped ensure both accuracy of interpretation and the preservation of anonymity. One participant used this opportunity to further clarify their statements or to request adjustments for improved neutrality or precision. The summary of each of the interviews can be found in Appendix B.2

Table 3.2: Codebook used for analyzing interviews and refining literature-defined challenges for the Dutch high-tech manufacturing sector

Code	Definition and inclusion/exclusion criteria
Addition	Interview insight introduces a new theme, aspect, or nuance not covered by the literature-based definition. <i>Include:</i> when a participant raises something genuinely new. <i>Exclude:</i> if the aspect is already implicit in the existing definition.
Specification	Interview insight makes the existing definition more specific to context, e.g., tailored to the Dutch high-tech manufacturing sector. <i>Include:</i> when a participant elaborates on how a challenge manifests. <i>Exclude:</i> if the clarification remains too general.
Contrast	Interview insight presents a view that contradicts or challenges the literature-based definition. <i>Include:</i> when a participant offers a divergent perspective. <i>Exclude:</i> if the difference is only in phrasing or emphasis.
Example	Interview insight provides a concrete case, anecdote, or illustration of a literature-defined challenge. <i>Include:</i> practical or real-world examples that clarify the challenge. <i>Exclude:</i> if the example is purely hypothetical or abstract.

In the second stage, the data was reorganized by challenge rather than by interviewee. All coded statements linked to a specific challenge were compiled and compared with the corresponding literature-based definition. Where discrepancies emerged, the interview data was prioritized, reflecting the belief that lived experiences from sector professionals offer critical context-specific nuance. While the literature served as a foundational framework, the interview insights brought in practical perspectives that grounded the definitions in real-world conditions. As a result, the final definitions are both theoretically informed and empirically validated, ensuring their relevance for the Dutch high-tech manufacturing context.

3.2.3. Results

Relevance of challenges

Based on the pre-interview survey completed by the interview participants, a ranking was created for the challenges identified in the literature. This ranking was done from both a short-term perspective (the next 5 years) and a long-term perspective (5 to 10 years), with each participant approaching the task from their own professional viewpoint. Figure 3.2 displays the average normalized rankings across all participants, showing the short-term rankings on the left and the long-term rankings on the right.

The results show that in both timeframes, the two cost-related challenges (challenges 1 and 2) were considered the most important. Managing regulation while remaining competitive was identified as a more pressing challenge in the short term, though it continued to be seen as important over the long term. Strategy-related challenges (challenges 4 and 5) stood out as being more relevant in the short term, along with the need to better understand how digital technologies affect sustainability. In the long term, however, the evolving nature of the Twin Transitions was viewed as a more significant challenge to successful implementation.

During the interviews, participants reflected on their survey rankings and discussed the importance of each challenge. A recurring insight was that the lack of focus on social sustainability was often ranked among the least important in the survey. However, once the concept of social sustainability was defined and explored during the conversation, most participants acknowledged its importance. Many emphasized the critical role of the ‘human factor’ in both digital and sustainability transitions. Although social sustainability was not commonly seen as a major barrier to initiating the Twin Transitions, it was frequently mentioned as essential to implementing them successfully. Several interviewees (A1, M1, P1, M2) stress that technology transitions must be human-centric and involve the workforce early to avoid disengagement or resistance, which is key to making the transitions effective according to the interviewees.

There is a notable difference in how challenge 13 is perceived in the short term versus the long term in the pre-interview survey. Interview participants view balancing regulation and competitiveness as a more pressing issue in the short term. In the long term, however, they consider it less of a challenge. While none of the interviewees provided a specific reason for why this challenge might become easier over time, they did indicate that due to ongoing regulatory uncertainty (challenge 12), it remains unclear how difficult it will be to manage competitiveness and compliance in the future (M2, M3).

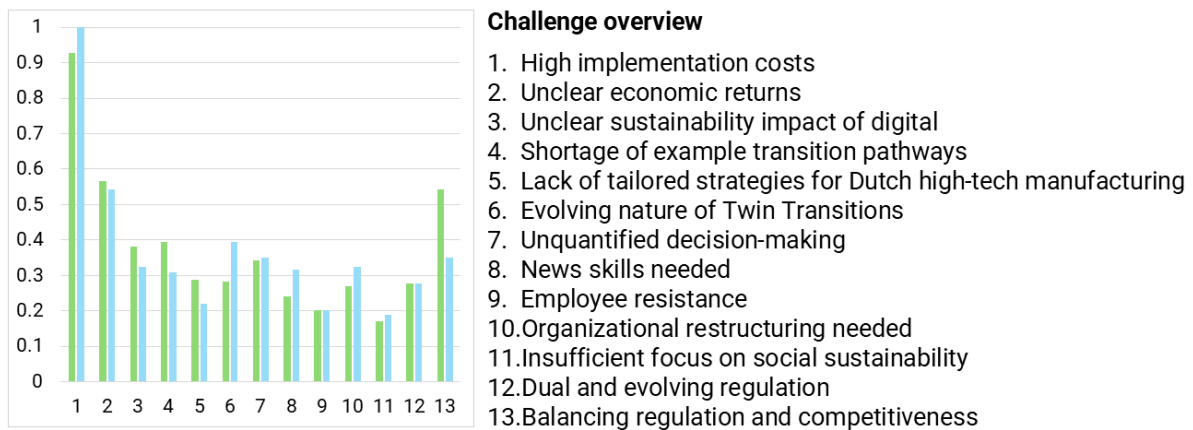


Figure 3.2: Pre-interview survey ranking of literature identified challenges by all the participants. In the green is the ranking for the short-term, in blue is the long-term ranking.

Overall, no challenge was seen as entirely unimportant. While some were viewed as more significant obstacles than others, all were recognized as presenting some level of barrier to the implementation of the Twin Transitions.

Connection between challenges

To explore whether some challenges act as root causes that drive most of the others, the connections between the challenges identified in the literature were compared with the insights from the interviews. If a few challenges appear to trigger or reinforce many of the others, this would suggest that focusing on these key challenges could help address the broader set of issues.

To map these relationships and explore possible hierarchies among the challenges, a Causal Loop Diagram was developed. Causal Loop Diagrams (CLDs), also known as System Thinking or Influence Diagrams, are effective tools for visualizing complex systems by mapping interactions, dependencies, and feedback loops (Morecroft, 2015). These diagrams illustrate how changes in one variable influence others, either reinforcing or counteracting effects, providing insight into system behavior.

Creating a CLD involves three key steps. First, the key variables must be identified. In this case, these variables correspond to the 13 challenges identified through structured review. Second, causal relationships between these variables must be determined. This involves analyzing how changes in one factor influence another, either directly or indirectly. Relationships are categorized as positive, where an increase in one variable leads to an increase in another (or a decrease leads to a decrease), or negative, where an increase in one results in a decrease in the other (or vice versa). Finally, feedback loops must be identified. These loops capture the cyclical nature of interactions within the system, where variables continuously influence one another over time. Positive feedback loops reinforce changes, potentially amplifying effects within the system, while negative feedback loops counteract changes, stabilizing the system.

Application method

The relationships between the identified challenges are determined based on Table B.3 in Appendix B.1. To establish these connections, studies that addressed multiple challenges were analyzed to assess whether they explicitly identified links between them. These findings were then cross-referenced with other studies to determine whether the same relationships were recognized elsewhere and were reviewed with the insights from interviews. If no study that discussed multiple challenges indicated a connection, nor an interviewee mentioned a connection between the challenges, the link was excluded from the analysis.

Results and conclusions of the CLD

Table B.5 in Appendix B.1 presents the identified causal links between challenges, indicating whether these relationships are positively or negatively reinforcing. Figure 3.3 provides a visual representation of these connections. The figure reveals that there are no root causes, no single challenge or small

set of challenges serves as the primary driver of all others. This suggests that all identified challenges must be considered when implementing the Twin Transitions in manufacturing companies.

The majority of the links identified in the literature were either confirmed or not contradicted by the interviewees. However, one link (between challenge 6 and challenge 1) was not supported. The literature suggests that changing technologies and sustainability impacts may lead to cost reductions over time, for example, through technologies becoming more accessible and affordable. Yet, interview participants consistently described the opposite: increased complexity, rising operational costs (especially for AI and cloud services), and ongoing organizational expenses. These findings suggest that, in practice, maturity-based cost reductions are not yet being realized.

At the same time, the interviews revealed a new connection not identified in the literature, namely between challenge 3 and challenge 2. Participants pointed out that if companies are unable to see or quantify the sustainability benefits of digital tools, they also struggle to calculate the potential economic returns. As a result, a reinforcing relationship exists between these two challenges: the lack of visibility into sustainability outcomes makes it harder to justify digital investments from a financial perspective.

Figure 3.3 also shows that nearly all links between challenges are positively reinforcing, meaning that addressing one challenge will indirectly contribute to resolving others. This indicates a lack of significant trade-offs, as efforts to tackle one issue will likely have broader benefits. The negatively reinforcing link, however, stems from external factors: the ongoing development of relevant regulations. Since these influences lie outside the control of manufacturing companies, they do not create direct conflicts in addressing the other challenges.

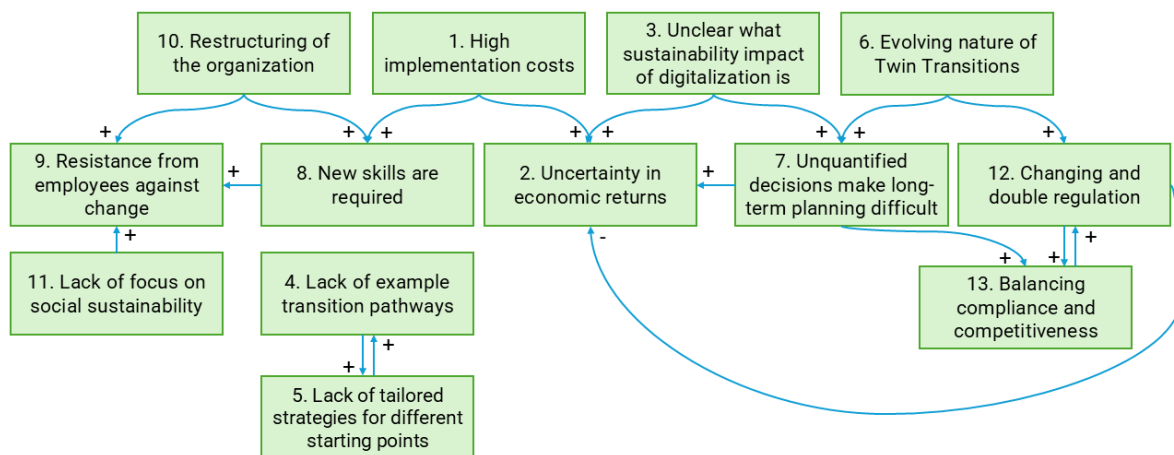


Figure 3.3: Causal loop diagram mapping the positive and negative reinforcement connections between the identified challenges in implementation of the Twin Transitions for manufacturing companies.

The interviews also confirmed that certain pairs of challenges are strongly interconnected and mutually reinforcing. Participants indicated that these challenges cannot be treated as separate issues, as they influence one another in a continuous loop.

The first pair is challenge 1 (high implementation costs) and challenge 2 (lack of understanding of economic returns). This was frequently described as a feedback loop by the interviewees. High costs discourage investment, but without investment, it is difficult to gain insight into possible returns. Several participants described this as a "chicken-and-egg" problem. Others pointed out that the organizational costs involved can be three to four times higher than technical costs, which makes it even more difficult for companies to justify these investments without concrete expectations of return. Overall, this loop of uncertainty reinforces hesitation and slows down progress.

A second strongly linked pair is challenge 4 (shortage of clear, practice-based transition pathways) and challenge 5 (lack of tailored strategies that address unique starting points). According to participants, the absence of concrete examples and roadmaps makes it difficult for companies to develop transition strategies suited to their specific situations. This gap leads to a lack of both practical guidance and strategic customization. One participant highlighted the shortage of transferable best practices, especially beyond the product level and into the supply chain. Another explained that while many companies are actively searching for guidance, most remain in an exploratory phase, and there is still little empirical knowledge about what strategies are truly effective. The two challenges were often linked

in participant responses; one interviewee noted that “everyone is reinventing the wheel,” and another used the metaphor of companies being on the same road from Rotterdam to Paris, but at very different stages of the journey. This illustrated the need for guidance that is adaptable to individual company circumstances. It was also noted that companies often face short-term operational challenges, such as high up-front costs and long payback periods, alongside longer-term concerns like accountability and sustainability goals. These operational and strategic dimensions combined make the transitions more difficult to manage effectively.

A third interlinked pair consists of challenge 12 (navigating dual and evolving regulations) and challenge 13 (managing regulations while remaining competitive). These challenges were described as being tied to the same underlying issue: regulatory uncertainty. Participants explained that constantly changing regulations create confusion, which in turn delays decision-making and strategic planning. One interviewee stated that frequent policy updates lead to hesitation, as companies are unsure what direction to take. Another pointed out that regulations often do not align with market incentives, meaning that compliance may not result in a competitive advantage, and may even lead to market disadvantages. A recurring concern was that sustainability-related legislation, such as the CSRD, creates ambiguity. While its intent is to drive sustainability, its evolving nature leads companies to question whether compliance brings real business value or is merely a formal obligation. One participant noted that recent amendments, like the Omnibus update, bought companies more time but also underscored how unsettled the regulatory environment still is. Another warned that unclear regulation, combined with fast-moving technologies, makes it difficult for companies to know whether current investments will remain relevant in the future. Several participants mentioned that this uncertainty prevents companies from making long-term commitments to sustainable technologies or strategies. These insights align with the literature’s view that evolving regulation presents not only a compliance issue, but also a strategic risk to competitiveness within the Twin Transitions.

3.3. Integrating literature and interview insights

Challenge 1: High implementation costs and uncertain economic returns form an intertwined barrier for Twin Transition investments in the Dutch high-tech manufacturing sector.

High implementation costs for digital transformation and sustainability, alongside uncertainty about their economic returns, combine to form a single, intertwined challenge. From a literature perspective, adopting new digital infrastructure (e.g., AI, cloud, robotics) and sustainable solutions (e.g., energy-efficient equipment, renewable energy sources) necessitate substantial initial investments (Benedetti et al., 2023; Sjödin et al., 2024; Stucki et al., 2024; Gulbrandsen-Dahl et al., 2024; Fouquet and Hippe, 2022). These expenditures frequently extend into underestimated operational expenses, compounding the burden when organizations pursue both digital and green transitions (Sjödin et al., 2024; Stucki et al., 2024; Elyasi et al., 2024; Chen et al., 2023; Fu and Xu, 2024), (P1). In the Dutch high-tech manufacturing context, however, uncertainty regarding whether these costs will yield tangible financial returns is often more decisive than upfront investment cost alone (M1; M2; A2). As M2 notes, “It’s a bit of a chicken-and-egg problem. If you can’t demonstrate returns, you don’t invest. But you need to invest to see any return.”

Many firms demand quick and demonstrable payback, usually within two to four years (M1; A2). This short time horizon intensifies the requirement for clear economic benefits, illustrated by A2’s statement: “If digitalization contributes to sustainability goals and leads to economic gain, such as cost reduction or operational efficiency, then it stays on the agenda. Otherwise, it disappears.” This stance also reflects shareholder expectations, where uncertain outcomes prompt boards to halt initiatives (A2). Although high implementation costs remain a concern, particularly for mid-sized firms that find it challenging to hire sustainability personnel or expand IT capacity (M3), the issue frequently revolves around proving these costs will pay off. Failures with projects such as ERP or robotics have created a “climate of distrust” (M1). As M1 explains, “If even we at [the research institute] don’t know what a digital product passport costs or delivers, companies certainly won’t invest in it,” underscoring the business-case-driven mindset.

Additional financial strains arise from ongoing operational costs, which sometimes exceed initial investment. P2 observes that “sometimes the run costs end up being higher than the implementation costs,” especially for cloud-based or AI-driven solutions. This reality forces firms to choose carefully where to allocate limited budgets, as “you can only spend your money once” (P2). When sustainability

initiatives are not yet economically viable, such as recycling complex chip components (P3), the lack of a clear business case further discourages investment, despite potential long-term advantages. Companies thus seek proven, efficient solutions rather than risking large sums without certainty of return (A2). Although the literature stresses that substantial expenditures can delay progress (Ortega-Gras et al., 2021; Breiter et al., 2024; Kekkonen et al., 2023; Benedetti et al., 2023), in Dutch high-tech manufacturing, ROI requirements and a risk-averse culture rooted in past project failures often pose a stronger disincentive. High upfront costs and unclear payback horizons are therefore tightly interwoven, impeding firms' willingness to move forward with both digital and sustainable transformations.

Challenge 2: The sustainability impact of digital technologies remains poorly understood by Dutch high-tech manufacturing companies.

In the Dutch high-tech manufacturing sector, the integration of digital transformation and sustainability remains a significant challenge. Historically, research on these two domains has developed separately, and only recently have efforts emerged to unify them under the concept of "Twin Transitions" (Benedetti et al., 2023). Despite this, "90% [of companies] see these as two separate domains. The definitions aren't aligned, the scope is unclear. . ." (A2). Even digitally advanced firms can fail to integrate their digital initiatives with holistic sustainability goals (M2), resulting in vague, uncoordinated efforts, although some early-stage integration is beginning to take shape (A1).

One of the reasons is the lack of transparency and clarity around the environmental impact of digital technologies. Many organizations still perceive digital solutions as "commodity-like and non-resource-intensive" (A1), and do not consider their environmental costs. This perception contributes to the broader issue that manufacturing companies often struggle to assess whether digital technologies support or hinder sustainability goals (Stucki et al., 2024; Kren and Lawless, 2024). While these technologies can boost efficiency, their environmental footprint remains a poorly understood trade-off (Chatzistamoulou, 2023; Kekkonen et al., 2023; Elyasi et al., 2024). P2 emphasizes that the sustainability impact of digital tools such as AI and cloud computing is not well understood or systematically included in decision-making. P2 gives a practical example: "Python is not the most energy-efficient programming language, but everyone uses it." This illustrates a broader lack of awareness about the energy and ESG impacts of widely adopted digital tools. P1 adds that "there is little transparency in the chain," especially when it comes to understanding the carbon footprint of AI data centers.

This uncertainty is echoed by M3, who points out that "companies are unsure what they can do with AI or how they can create value from and with sustainability initiatives." M3 underscores the broader difficulty of identifying which digital tools or sustainability measures will actually yield results.

Despite growing awareness of sustainability as a priority, Dutch high-tech manufacturers often fail to systematically balance the environmental costs and benefits of their operations. Their carbon footprints and broader environmental impacts are rarely tracked or evaluated (P1, P2). On a macroeconomic level, the energy impact of digital transformation depends on complex factors such as sector growth, energy efficiency gains, economic trends, and structural industry shifts (Kürpick et al., 2024).

In practical terms, implementation of sustainability, especially in relation to circular economy strategies, remains limited. M1 notes that while sustainability is "on the agenda," actual progress is hindered by the sector's reliance on fragmented, manual processes such as Excel sheets. This reflects what M1 describes as an "infancy" in practical implementation. Many firms, even those motivated by sustainability goals, continue to use these outdated systems, further complicating efforts to integrate digital transformation and circularity.

Challenge 3: Dutch high-tech manufacturing companies struggle with the absence of example Twin Transition pathways, while simultaneously requiring flexible, tailored strategies that address their unique operational contexts and varying maturity levels.

A major strategic challenge is the intersection of the shortage of clear, practice-based example transition pathways (Benedetti et al., 2023; Trevisan et al., 2024; Chatzistamoulou, 2023; Diodato et al., 2023; Chen et al., 2023; Kirov, 2023; Perossa et al., 2023; Ortega-Gras et al., 2021) and the need for flexible, company-specific strategies that address varying degrees of organizational readiness and operational complexity (Spaltini et al., 2024a; Kürpick et al., 2023, 2024; Abilakimova et al., 2025). While the literature acknowledges that manufacturers often lack robust models to integrate digital transformation and sustainability, interviewees emphasize that this gap is even more acute in the Dutch high-tech domain due to sector-specific factors like long equipment lifespans, the use of critical raw materials, and intricate value chains (A1).

According to A1 and A2, many companies in this sector remain in an exploratory phase, focusing on small pilot or prototype Twin Transition projects (for example, testing product innovations) rather than developing comprehensive, step-by-step Twin Transition roadmaps. A1 further highlights the practical difficulty of conducting legacy and new operations in parallel, arguing that “You have to manage it in parallel... you cannot just shift everything at once.” This insight goes beyond the literature by underscoring a critical, hands-on barrier: even if example pathways existed, firms would still struggle with the phasing of old and new systems. M1 points to a similar implementation gap, noting that in circular economy practices, some manufacturers merely use Excel to track critical metrics, an example of fragmented attempts that lack cohesive, well-documented methodologies.

Simultaneously, the interviews show that Dutch high-tech manufacturers must tailor solutions to their unique maturity levels, which vary substantially. P1 observes that some companies are still removing outdated systems, while others are experimenting with advanced digital tools like AI or GenAI. P2 underscores how firms frequently perceive themselves as too unique for example frameworks, yet “everyone is on the same road from Rotterdam to Paris”, indicating that while shared transition pathways could provide essential benchmarks, they need to be adaptable enough to accommodate different stages, resources, and market pressures.

M3 expands on this theme, highlighting high initial costs, extended payback periods, and a lack of clear sector-wide roadmaps as major stumbling blocks. The consequence is a tendency toward short-term operational fixes rather than holistic strategies that reconcile immediate performance needs with long-term accountability for both digital transformation and sustainability (Spaltini et al., 2024a).

Taken together, these insights show that purely “copy-paste” models fall short because they fail to incorporate the distinct resource constraints, technologies, and regulatory environments in Dutch high-tech manufacturing (A2, M3). Yet at the same time, the near-total absence of well-documented, sector-specific examples forces companies to continually “reinvent the wheel” (M2). Thus, this integrated challenge arises from the tension between a pressing need for more example, practice-based transition pathways, backed by concrete best practices and benchmarks, and the equally urgent requirement for customizable, nuanced approaches that factor in varying maturity levels, operational realities, and sustainability obligations.

Challenge 4: The evolving nature of the Twin Transitions adds complexity to their implementation for Dutch high-tech manufacturing companies.

The Twin Transitions involve constantly evolving domains: in the digital transition, new technologies are continuously developed and introduced, while in the sustainability transition, new impacts emerge across supply chains (Abilakimova et al., 2025; Trevisan et al., 2024; Chatzistamoulou, 2023). This dynamic external environment, including technological advancements and shifting customer needs, complicates implementation (Tabares et al., 2025; Findik et al., 2023; Benedetti et al., 2023), (P1). Specifically within the Dutch high-tech manufacturing sector, a constant influx of new concepts (e.g., “digital product passports,” “control towers”) creates confusion and uncertainty about what is truly essential (A1). Many companies are still in a discovery phase, experimenting to determine whether and how the Twin Transition should be pursued (A2). P2 echoes this point, noting that while significant progress has been made in digital transformation, especially with technologies like Digital Twins, companies are still constrained by the legacy systems and the hype cycle that needs to be navigated before full adoption.

Although some Dutch high-tech manufacturers are already exploring advanced technologies such as AI and GenAI to enhance productivity and competitiveness (P1), others remain at lower levels of digital maturity, still focusing on Industry 3.0 automation and underutilizing data (M1). External market dynamics, especially regulatory pressure and shifting customer expectations for transparency and sustainability, further influence how quickly these companies adopt digital and sustainable solutions (M2; P1). Uncertainty surrounding technological evolution and market conditions often leads them to delay adoption (Kren and Lawless, 2024).

Challenge 5: Unquantified decisions within the Twin Transitions complicate long-term decision-making.

A major challenge in the Twin Transitions is the lack of quantification in decision-making, which complicates long-term strategic planning (Kürpick et al., 2023; Tabares et al., 2025; Fouquet and Hippe, 2022). In the Dutch high-tech manufacturing sector specifically, interviewees emphasize that environmental and sustainability benefits are particularly difficult to quantify compared to economic returns (A1). This aligns with the broader literature: current reporting and assessment standards remain opaque, making

it difficult for manufacturers to evaluate their progress (Kürpick et al., 2024; Kren and Lawless, 2024). As a result, many struggle to measure their performance in digital and green initiatives (Abilakimova et al., 2025), and, as A1 puts it, “[Sustainability KPIs]... they are not on top of that yet.”

Several interviewees highlight that companies are not yet able to fully track sustainability impacts or quantify their progress. For instance, they often rely on manual processes in Excel to track product-level CO₂ data or component-level information (M1). Moreover, certifying and tracking sustainability in supply chains is hindered by a lack of clarity, transparency, and data-sharing barriers, with technical and proprietary concerns preventing information from flowing freely between partners (M2).

Uncertainty around the gains of both digital and sustainability investments heightens organizational indecision. As M3 illustrates: “If we invest in AI, will we reduce product development from 14 to 8 months? Or just to 13?” Similar ambiguity surrounds the challenge of evaluating their full environmental impact (P1). Reducing this uncertainty requires clear, quantitative metrics and indicators (Peças et al., 2023). Yet, M3 points out that companies often lack clarity on what data they even need, particularly in relation to sustainability.

P2 further notes that despite advances in digitalization, poor data quality continues to hinder the integration of digital and sustainability efforts. P3 echoes this, observing that many organizations still struggle with foundational data issues, making it difficult to move beyond pilot stages: “Use cases sound promising in theory, but quantifying exact savings or efficiency gains remains difficult.”

Within sustainability, P2 highlights that quantification is particularly challenging at the process level. While environmental impacts such as energy use and CO₂ emissions are relatively straightforward to measure, social and governance aspects are far harder to quantify and integrate into business cases. This difficulty is captured by the insight: “Not everything that is measurable is comparable,” emphasizing the need for standardized units to make diverse sustainability metrics meaningful for decision-making in Dutch high-tech manufacturing.

Challenge 6: The Twin Transitions demand new skills from both the company and its employees.

The Twin Transitions demand new skills from both companies and their employees (Trevisan et al., 2024). These include expertise in digital technologies, resilience, green technologies, and internal organizational management (Trevisan et al., 2024; Tabares et al., 2025). Employees must learn to work with new software and machinery while also developing the ability to analyze and interpret data (Trevisan et al., 2024; Kirov, 2023). At an organizational level, companies need dynamic capabilities to adapt their business practices in response to rapidly changing environments (Breiter et al., 2024; Sassanelli et al., 2024).

In the Dutch high-tech manufacturing sector specifically, these skill requirements are further complicated by uneven levels of digital maturity. Many companies still operate with conventional automation systems and isolated digital tools (M1; M2). Integration challenges across ERP, PLM, and MES systems remain widespread, making it difficult for companies to fully benefit from digital transformation without substantial investments in both technology and staff training (M1). As a result, companies often lack the internal expertise to develop, implement, or even maintain more advanced digital and green technologies (M2; P2).

Moreover, there is often little clarity about which specific types of expertise are required to implement digital and sustainability initiatives effectively, particularly in the Dutch high-tech manufacturing sector where hardware and software integration is complex and highly context-specific (M3). This further reinforces the need for multi- and interdisciplinary collaboration across departments, rather than leaving the responsibility solely to top management (Christmann et al., 2024), (M3).

In addition, many organizations face significant talent shortages, particularly as they attempt to bridge the gap between maintaining legacy systems and adopting new technologies. As one interviewee noted, “It’s incredibly difficult... The new generation isn’t interested in outdated technologies” (P1). This highlights the dual challenge of preserving legacy knowledge while cultivating new digital competencies. Companies that support a learning culture, support experimentation, and invest in their people are more likely to navigate these transitions successfully (P1).

However, the lack of internal knowledge and competence in developing or utilizing digital technologies continues to hinder progress (Gulbrandsen-Dahl et al., 2024), often requiring the support of external experts (Kürpick et al., 2023).

Challenge 7: Resistance from employees may arise due to the extensive changes required by the Twin Transitions.

Digital transformation drives continuous change and creates tensions between the "old" and the "new" (Christmann et al., 2024). Industry 4.0 may lead to deregulation of employment relationships, pressure for constant availability, and new ways of evaluating employee performance (Kürpick et al., 2023). Employees often resist these changes due to fears of the need for retraining, or unfamiliarity with new digital tools (Findik et al., 2023; Benedetto and Forleo, 2024). This fear of the unknown and the need to acquire new skills is confirmed by interviewee M3, who emphasizes that such uncertainty is a significant source of resistance in Dutch high-tech manufacturing firms. Similarly, P2 underscores the presence of cultural resistance, noting that people are often inherently conservative and "constrained by the past," particularly when navigating the hype cycle of digital adoption.

However, unlike the literature, several interviewees suggest a reversed emphasis in the Dutch context. A2 indicates that resistance is often less pronounced toward digital transformation and more prevalent in the sustainability domain. This is attributed to sustainability's abstract character and its perceived lack of direct operational relevance, especially among technical and shop floor staff (A2). While technical teams reportedly show openness toward change, A2 notes that strategic leadership sometimes delays action unless change becomes urgent.

The literature suggests that sustainability transformation can act as a motivating force for employees (Christmann et al., 2024), but this is not universally supported by the interview data. A2 describes sustainability efforts as primarily compliance-driven and lacking a compelling business case, resulting in disengagement rather than motivation. While M3 acknowledges that sustainability awareness is rising in some firms, and may offer an entry point for engagement, it does not yet function as a consistent motivator across the sector. Both P1 and P2 stress the importance of a supportive culture, where learning, experimentation, and people development are encouraged. Companies with such a culture are more likely to overcome resistance and succeed in their transformation efforts.

Challenge 8: The Twin Transitions may necessitate organizational restructuring in Dutch high-tech manufacturing companies.

A successful Twin Transition requires a shift in how companies view their role in the value chain and how they create value (Sjödin et al., 2024; Stucki et al., 2024). This involves fundamental changes in thinking about industrial processes, supply chain management, and service delivery (Abilakimova et al., 2025). Companies must integrate both technological and managerial transformations while supporting cross-functional collaboration (Spaltini et al., 2024a).

In the Dutch high-tech manufacturing sector specifically, this restructuring often manifests in breaking down longstanding silos between departments, especially between business and IT, and across digital and sustainability domains. Participants emphasized that siloed structures severely hinder cross-departmental collaboration, an essential element of Twin Transition success. As A2 noted, "The moment a topic spans multiple departments, you have a problem," pointing to real-world difficulties in integrating innovations, and sustainability into existing workflows. P1 echoed this, observing that traditional boundaries between business and IT are dissolving as automation and digital technology adoption grow, requiring new governance models and consolidated roles.

While the literature highlights the importance of collaboration across the supply chain (Abilakimova et al., 2025), the interviews reveal that even internal collaboration, such as aligning sustainability with digital initiatives, is still often lacking. To operationalize strategies like circularity and reuse, companies must bridge departmental divides (P2), moving from a theoretical understanding of sustainability's strategic value to practical, cross-functional implementation. This often entails parallel governance systems, especially in IT and data management, where legacy models must coexist with emerging structures (A1). Implementing the Twin Transitions therefore demands not just structural change but also cultural and procedural shifts that promote integrative thinking and collaboration across all organizational layers.

Adopting an open innovation approach may help companies respond to evolving market demands (Re et al., 2024), but it also requires a careful balance between collaborative ("commoning") and proprietary ("enclosure") organizational strategies (Sareen et al., 2023). M3 believes that environmental data like energy or water use can usually be shared without giving away technical trade secrets. "You can separate the two," M3 argues. However, verifying data from suppliers and integrating it across long and specialized supply chains remains a huge challenge.

Challenge 9: There is insufficient focus on social sustainability within the Twin Transitions, as the link between environmental sustainability and digitalization is clearer and more measurable.

There is insufficient focus on social sustainability within the Twin Transitions, particularly in the Dutch high-tech manufacturing sector, as the link between environmental sustainability and digital transformation is clearer. According to P3: “You can’t leave social sustainability undefined. It’s about the right way of working in all its dimensions.” Consequently, companies often prioritize economic and environmental sustainability over social sustainability, especially when digital transformation drives sustainability efforts (Abilakimova et al., 2025).

P2 underscores the difficulty of quantifying social and governance impacts, particularly at the process level, making them harder to measure and incorporate into business cases than environmental indicators such as energy use and CO₂ emissions.

Challenge 10: Navigating evolving Twin Transition regulation while preserving competitiveness is an implementation barrier for the Dutch high-tech manufacturing sector.

Navigating frequently evolving regulations governing the Twin Transitions while striving to remain competitive is a compounded challenge in the manufacturing sector (Spaltini et al., 2024b; Abilakimova et al., 2025; Sjödin et al., 2024). Although the literature distinguishes between the difficulty of keeping up with changing regulations (Re et al., 2024; Chatzistamoulou, 2023; Tabares et al., 2025; Kren and Lawless, 2024) and the challenge of balancing these regulatory demands with competitiveness (Spaltini et al., 2024b), interviewees in the Dutch high-tech manufacturing sector perceive these aspects as tightly interconnected. They emphasize that regulatory uncertainty, including changes in sustainability standards (e.g., CSRD) and inconsistent enforcement, causes companies to delay or minimize investments in climate-friendly technologies and broader sustainability measures (A1; A2; M2; M3; P2; P3). This regulatory flux not only increases compliance risks and costs (A1) but also complicates long-term strategic planning (M3; P3). As M3 describes it, a vicious cycle arises where firms are reluctant to invest without a stable regulatory framework, yet regulations are expected to drive precisely those investments.

Inconsistent or frequently modified policies in the Netherlands undermine confidence, making firms wary of investing in sustainability initiatives that might later become misaligned with updated requirements (A1; A2; M2). M3 explains that this uncertainty “creates delay, because companies don’t know what to bet on.” Interviewees also note that recent regulatory postponements and perceived weakening of sustainability directives (e.g., CSRD, CS3D) momentarily relieve immediate pressure but prolong uncertainty about future obligations (A2; P3).

Further intensifying the issue, Dutch high-tech manufacturers feel pressured to meet increasingly stringent environmental demands while competing globally, particularly against regions with more lenient or less rapidly evolving regulatory landscapes like the U.S. “There, it’s more drill baby drill,” M3 notes, referencing a quote by Donald Trump. In the Netherlands, higher energy prices, partly due to decarbonization, have already created a competitive burden (M3). This discrepancy undermines the “level playing field” and creates strategic dilemmas for Dutch high-tech manufacturing companies.

3.4. Selection of challenges to address with the decision-support tool

When designing a decision-support tool to guide Dutch high-tech manufacturing companies through the Twin Transitions, it is important to select from the list of implementation challenges identified in Section 3.3 those challenges that align with what such a tool can effectively address.

A decision-support tool primarily facilitates structured reasoning, trade-off analysis, and informed decision-making. For these functions to be effective, companies must have a basic understanding of the problem they are addressing. The tool provides the most value in situations where companies know what they want to achieve but face uncertainty about how to reach those objectives. This uncertainty often stems from insufficient knowledge, lack of data, or limited predictability regarding the impact of digital technologies on sustainability outcomes.

On the other hand, challenges characterized by unclear or ill-defined objectives are less suitable for the early design phases of a decision-support tool. When goals are vague, the problem space lacks the necessary structure for informed decision-making. Such challenges require sense-making and conceptual clarification, rather than analytical support through a decision-support tool. Similarly, when both

the technological solutions and the necessary requirements are already well known or readily available, developing a specialized decision-support tool is not justified. In these cases, best-practice guidelines, training programs, or change management approaches offer more appropriate solutions.

Background information on the Stacey Matrix

To identify which challenges are most suitable for a decision-support tool (specifically, those with clear goals but uncertainty in how to achieve them) the Stacey Matrix can be applied. Originally developed in the early 1990s, the Stacey Matrix provides a conceptual framework for understanding and managing complexity in decision-making (Stacey, 2012). An adapted version of this matrix, mapping complexity along the dimensions of technology and requirements, is often used in the context of organizational digital transformations (Stacey, 2012). Given that this study focuses on implementing the Twin Transitions at the company level within Dutch high-tech manufacturing firms, the Stacey Matrix offers a relevant method for categorizing implementation challenges.

This framework defines complexity along two axes. The requirements axis reflects the clarity of what needs to be achieved, while the technology axis represents how well the methods or tools needed to achieve these goals are understood (Stacey, 2012). When both dimensions are well defined, challenges are considered simple and can be addressed using established best practices. If the objectives are clear but involve unfamiliar technologies, the problem becomes complicated and requires expert analysis. Complexity increases when either the goals or the technological means are uncertain, demanding iterative and experimental approaches. When both the requirements and the technology are unclear, the challenge enters the chaotic domain, necessitating highly adaptive strategies.

Applying the Stacey Matrix to Twin Transitions challenges enables a structured assessment of complexity and control. Challenges categorized as simple or complicated typically fall within a company's direct influence, as existing solutions or developable approaches are available (Stacey, 2012). In contrast, complex and chaotic challenges often lie beyond direct control due to factors such as emerging technologies, shifting objectives, or external uncertainties like evolving regulations (Stacey, 2012). Distinguishing between these categories supports more effective strategic prioritization.

In this way, the Stacey Matrix not only helps categorize implementation challenges but also highlights where a decision-support tool can have the greatest impact: in situations where goals are clear, but the path to achieving them is uncertain. This prioritization ensures that the design of the tool is closely aligned with the specific challenges Dutch high-tech manufacturing companies face when translating digital transformation into measurable sustainability outcomes.

3.4.1. Application of the Stacey Matrix

Each of the challenges identified in Section 3.3 was analyzed using both literature sources and insights from the conducted interviews. The interview data served to validate whether, in practice, each challenge exhibited clear or unclear requirements and involved known or unknown technologies. This evaluation is presented in Table B.6 in Appendix B.3, which details the Stacey categorization of each challenge as assessed by individual interview participants. Additionally, Table B.7 in Appendix B.3 presents the aggregated results, summarizing how the average interview responses classify each challenge, alongside the underlying rationale and the degree to which these assessments are supported by existing literature. The overall findings are visualized in Figure 3.4.

As shown in Figure 3.4, the majority of challenges within the Twin Transition context are situated in either the complicated or complex domains. This indicates that while certain issues can be addressed through expert analysis and customized solutions, many challenges are characterized by significant uncertainty, interdependencies, and the absence of straightforward answers. Only a single challenge was categorized as simple, suggesting that few issues are easily solvable through established procedures or best practices. A small number of challenges, particularly those associated with social sustainability and the rapidly evolving dynamics of the transition, approach the chaotic domain, where both clear direction and stability are lacking.

From Figure 3.4 it can also be observed that when it comes to the clarity of requirements, the picture is mixed. While some challenges have well-defined goals and expectations, others suffer from ambiguity. In challenges related to strategic alignment, sustainability impact, or regulatory navigation, technologies are often perceived as unknown, not due to their absence, but because their effectiveness, integration, or long-term impact remains uncertain.

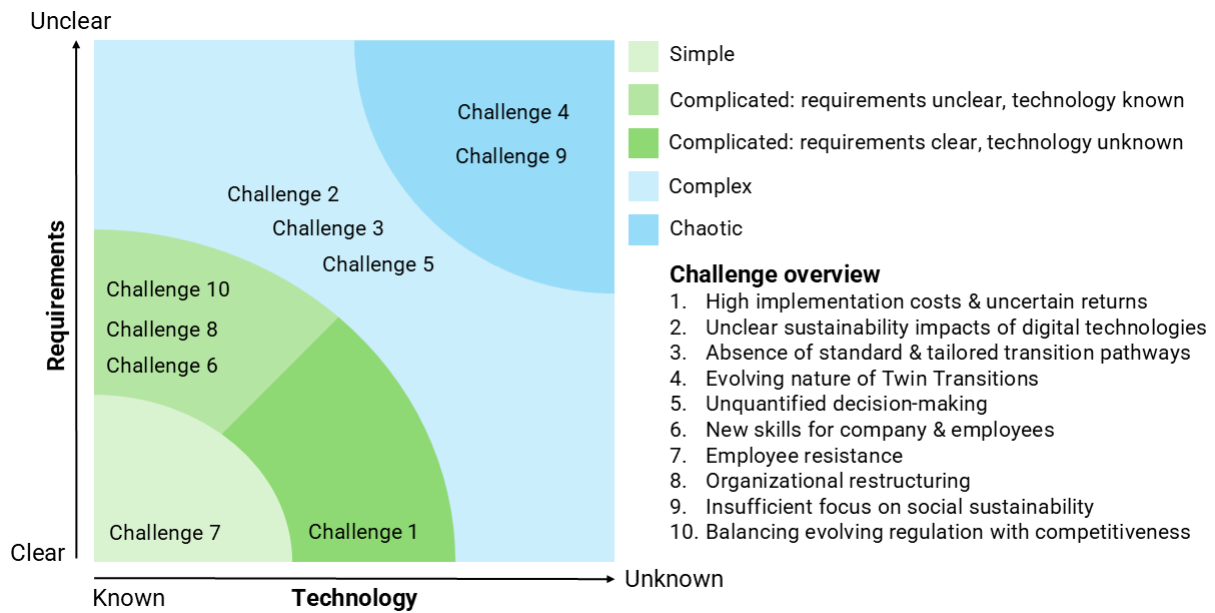


Figure 3.4: Stacey Matrix, based on Stacey (2012) with the re-categorization of the challenges following the input of the interviewees.

3.4.2. Stacey Matrix implications for challenge selection

Since the challenges addressed by a decision-support tool should have well-defined requirements but lack clear solutions (where decision-support can provide value), the categorization in Figure 3.4 shows that challenges 1, 2, 3, and 5 are suitable for the decision-support tool for the Twin Transition implementation.

Challenge 1 focuses on high implementation costs and uncertain economic returns, which are major barriers to investing in Twin Transition technologies. While the technologies themselves (such as AI and cloud computing) are relatively well known, the long-term financial implications, especially the return on investment, remain uncertain. The requirements, in terms of what companies want to achieve through these investments, are clear. This challenge falls into the complicated domain of the Stacey Matrix, where both the problem and the possible solutions are somewhat understood, but require analysis, expertise, and planning. Therefore, this challenge aligns well with the goal of a decision-support tool.

Challenge 2, which highlights the limited understanding of the sustainability impact of digital technologies, aligns closely with the tool's core purpose. Companies recognize the importance of understanding the ESG effects of their digital investments (the requirements) but currently lack the tools and data to do so. The decision-support tool can directly address this gap by helping organizations assess both positive and negative sustainability impacts, thus enabling informed trade-offs.

Challenge 3, which deals with the absence of standard Twin Transition pathways and the need for tailored strategies, also strongly aligns with a decision-support approach. While this challenge involves diverse company contexts, the underlying need is for guidance that can adapt to different operational setups. A well-designed tool could serve as a customizable framework to help companies align digital ambitions with their unique sustainability targets, even in the absence of universal roadmaps.

Challenge 5, concerning the difficulty of making long-term decisions due to unquantified factors, is also well-suited for support through a decision-support framework. Here, the problem is not a lack of intent but a lack of meaningful metrics and indicators. A tool that makes intangible aspects measurable, such as projected sustainability outcomes of digital strategies, can empower decision-makers in Dutch high-tech manufacturing companies to compare options and align their choices with long-term goals.

3.5. Phase 1 summary

Sub-research question	What are the challenges faced by Dutch high-tech manufacturing companies in implementing the Twin Transition?
Structured literature review	•Applied the PRISMA methodology to systematically screen over 800 academic articles; 34 were selected for in-depth analysis. •Identified 13 key challenges related to implementing the Twin Transition in the manufacturing sector.
Semi-structured interviews	•Conducted 8 interviews with experts from Dutch high-tech manufacturing, including representatives from academia, industry, and umbrella organizations. •Specified the literature-based challenges with interview insights. •Developed a causal loop diagram based on the interviews to map interconnections between challenges •Specified the literature challenges to 10 Dutch high-tech-specific challenges
Application of the Stacey Matrix	Used the Stacey Matrix framework to categorize challenges based on the degree of certainty in requirements and the degree of certainty in the method to address the challenge, to select the relevant challenges to be addressed with the decision-support tool
Chapter results	Identified four key challenges (<i>1, 2, 3 and 5 from Stacey Matrix, Figure 3.4</i>) appropriate to be addressed with a decision support tool: 1. High implementation costs and uncertain economic returns 2. Unclear sustainability impacts of digital technologies 3. Absence of (tailored) transition pathways 4. Lack of quantified decision-making for balancing sustainability and economic trade-offs

4

Phase 2: Defining the requirements

To develop an effective solution for the identified Twin Transition challenges, it is important to first define clear requirements for the decision-support tool. These requirements will guide the design process and later help evaluate how well the tool works (Johannesson and Perjons, 2014, p. 107). In the design science research methodology described by Johannesson and Perjons (2014), this step is formalized as the second phase: defining requirements. This phase focuses on identifying the key features the tool must have to successfully address the problem.

Accordingly, this chapter addresses **sub-research question 2**: *“What functional, structural and contextual requirements must the decision-support tool meet to support the Dutch high-tech manufacturing sector in addressing the identified Twin Transition implementation challenges?”*

Requirements are categorized into three types (Johannesson and Perjons, 2014, p.106-109):

- **Functional requirements:** Describe what the artefact should do, based on stakeholder needs and the specific goals of the problem. These are often tailored to the setting in which the artefact will be used.
- **Structural requirements:** Concern the internal composition and organization of the artefact, such as its modularity, coherence, and architecture.
- **Contextual (or environmental) requirements:** Focus on how well the artefact fits into its intended use context, including aspects like usability, clarity, and performance.

According to (Johannesson and Perjons, 2014, p.109-111), defining requirements typically involves two closely related stages:

1. **Conceptual description:** The decision-support tool is described at a high level to provide a general idea of what the solution might look like.
2. **Requirements elicitation:** Based on stakeholder needs and interests, more detailed and specific requirements are developed.

In line with this approach, this chapter first presents a conceptual vision of the decision-support tool by outlining the artefact’s core idea. It then refines this vision through stakeholder interviews, translating broad concepts into concrete design requirements.

4.1. Outlining the artifact

4.1.1. Translating the selected challenges into functional requirements

Once the challenges that the decision-support tool needs to address were identified, its high-level purpose was refined to the following:

This tool acts as a bridge between the digital manufacturing and sustainability domains within Dutch high-tech manufacturing companies. It is designed to facilitate strategic conversations on how digital technologies can be leveraged to drive sustainability efforts. By creating awareness of the broad, systemic sustainability impacts of digital manufacturing technologies, the tool supports companies in decision-making to navigate the Twin Transition. The tool serves as a decision-support mechanism that translates high-level Twin Transition aspirations into actionable operational decisions tailored to each company's specific context.

For each challenge identified in Section 3.4.2, a corresponding conceptual solution was developed. These solutions define the main goals of the tool and outline its intended structure and functionality. Following Design Science Research guidelines from (Johannesson and Perjons, 2014, p.107-108), these initial descriptions were kept abstract enough to allow for creative thinking, while still being concrete enough to guide the definition of requirements. The focus was on integrating capabilities that align strategically with firms' needs for sustainability and digital transformation, rather than isolating separate technical components.

Each of these conceptual solutions was then translated into one or more core functional requirements. These describe what the tool must be able to do to fulfil its intended purpose and were based on insights gathered during the interviews referenced in Section 3.2, as recommended by DSR for ground-requirement development in existing knowledge (Johannesson and Perjons, 2014, p.111).

To ensure these requirements could be practically implemented, each was further refined into a set of sub-requirements. These specify the more detailed functions the tool must support to meet its broader goals. This breakdown was guided by the researcher's application of design thinking principles.

Table 4.1 provides an overview showing how each challenge was addressed through a conceptual solution, translated into a functional requirement, and then further developed into specific sub-requirements.

Table 4.1: Overview of how the identified challenges from Phase 1 are translated into functional requirements using a step-wise approach: starting from the challenge, followed by solution formulation, then identifying the requirement, and finally specifying any sub-requirements.

Challenge	Solution	Requirement	Sub-requirement
Challenge 1: High implementation costs and uncertain economic returns present an inter-related barrier to Twin Transition investments.	Insight into the economic implications of investing in digital technologies that affect sustainability performance.	The tool provides insight into the financial risks and returns of Twin Transition investments.	The tool includes projected returns from implementing digital technologies (e.g. AI, cloud) in a Twin Transition context.
			The tool allows companies to compare alternative investment paths based on sustainability and cost-effectiveness.
Challenge 2: The sustainability impacts of digital technologies are not well understood by Dutch high-tech manufacturing companies.	A method to help Dutch high-tech manufacturing companies assess the sustainability impacts of specific digital technologies.	The tool maps the positive and negative sustainability impacts of digital technologies used in the Dutch high-tech manufacturing sector.	The tool enables assessment across various sustainability dimensions for digital technologies used in high-tech manufacturing.
			The tool shows both the direct and indirect sustainability impacts of digital tools.
			The tool facilitates side-by-side comparisons of digital transformation options based on sustainability trade-offs.
Challenge 3: Dutch high-tech manufacturing companies struggle with the absence of standard Twin Transition pathways, while also requiring flexible and tailored strategies.	An example Dutch high-tech manufacturing sector transition pathway using digital technologies to advance sustainability performance.	The tool maps the next steps of the sustainability transition specific to Dutch high-tech manufacturers.	The tool links digitalization efforts to corresponding sustainability goals in a stepwise format.
		The tool is adaptive to the specific context of a Dutch high-tech manufacturing company.	The tool identifies the resources needed for different implementation dimensions.

Challenge	Solution	Requirement	Sub-requirement
			The tool supports different starting points in the Twin Transition pathway depending on the level of digital and sustainability maturity.
			The tool supports different pathways depending on the size of the company.
			The tool supports different pathways depending on the position of the company in the supply chain (upstream vs. downstream).
			The tool supports different paces of transformation, ranging from incremental to radical.
Challenge 4: Unquantified factors within the Twin Transitions complicate long-term decision-making.	A structured evaluation system that supports evidence-based long-term sustainability decision-making through key metrics.	The tool enables quantification of Twin Transition-related decisions and their long-term effects.	The tool provides quantitative KPIs for tracking sustainability progress linked to digital transformation.
			The tool supports scenario modeling to explore long-term impacts of different digital strategies.

4.1.2. Defining structural requirements based on a literature review

To identify the structural requirements that support the tool's functions, as defined in the functional requirements of the previous section, a review was conducted of both academic and grey literature. This review focused specifically on models developed for organizational transformations, aiming to understand how models that address similar functions as outlined in Section 4.1.1 and translate these functions into structural components. By analyzing these literature-based examples, a comprehensive overview of potential structural requirements for the decision-support tool was developed.

The initial literature search concentrated on general organizational transformation decision-support models. This choice was made because, for the Twin Transition context, no existing decision-support models were available that directly address the integrated challenges of both digital transformation and sustainability in company transformation. Models focused solely on digital or manufacturing transformations tended to address mostly technical implementation aspects, while models addressing sustainability transformations risked introducing a bias by prioritizing sustainability over the integrated nature of the Twin Transition. Given these limitations, it was decided to use general organizational transformation decision-support models as a foundation. These models were then evaluated for their relevance to the Dutch high-tech manufacturing Twin Transition context by aligning their structural components with the functional requirements specified in Section 4.1.1.

Structured review methodology: PRISMA approach for identifying research articles

This structured literature review follows the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) methodology as described in Section 2.3.1. Figure 4.1 details how the four steps are applied to identify suitable articles containing organizational transformation models to identify their structural components. Appendix C.1.1 gives a more in depth description of how each step was done following the PRISMA methodology specifically for this literature review. A detailed overview of the included papers is provided in Appendix C.1.2, Table C.3.

Translating existing models into structural requirements

To identify relevant structural requirements for the proposed decision-support tool, each selected model from the literature was analyzed to identify its primary functions, what the model is designed to accomplish. For each function, the structural characteristics used to support it were examined, with a focus on how each function is implemented in practice. This analysis is summarized in Table C.3, Appendix C.1.

Each function from the literature was then matched to a corresponding functional requirement for the decision-support tool, as defined in Section 4.1.1. The structural characteristics from the literature were translated into structurally appropriate equivalents for the proposed tool. This process provided a

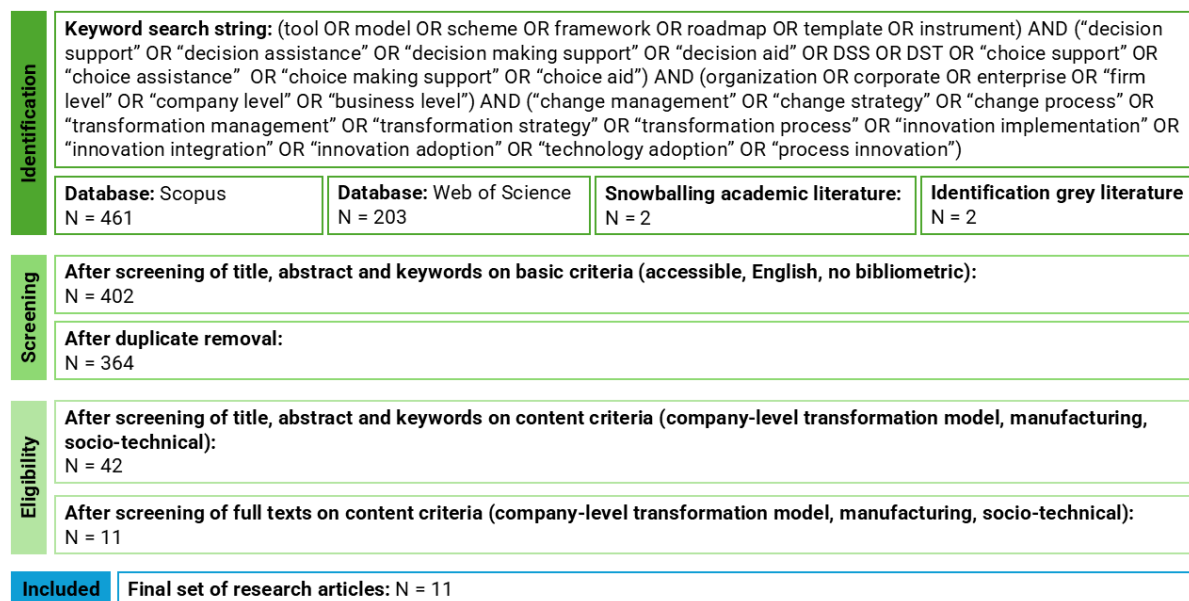


Figure 4.1: Identification of relevant research papers following the PRISMA methodology, consisting of four different stages.

set of structural requirements that directly support the tool's functional requirements, based on tested elements from existing models. An overview of this can be found in Table C.4 in Appendix C.1.

The resulting list of structural requirements was then reviewed to assess two aspects: which functional requirements were fully supported by literature-based structures, and which were not. All functional requirements were covered, but the number of structural options per function varied. Some had only one suitable structural requirement, for example, "the tool shows both the direct and indirect sustainability impact" (from the model by Zhang and Gu (2021)) and "the tool supports scenario modeling to explore long-term impacts of different digital strategies" (from the model by Accenture (2020)). Others were supported by multiple structural options, such as "the tool allows companies to compare alternative investment paths based on sustainability and cost-effectiveness," which had six possible supporting structures (from the models by Macedo et al. (2024), Utama et al. (2024), two from Forcina et al. (2024), Zhang and Gu (2021) and from Accenture (2020)).

The analysis also examined structural requirements that appeared in similar forms across different models. When two or more requirements exhibited methodological similarity, they were consolidated into a single structural version. For example, two variations of using TOPSIS for comparison were merged into: "the tool uses TOPSIS to determine how close the solutions are to the ideal situation (e.g., maximum sustainability impact, maximum cost-effectiveness), so they can be compared" (from the model by Forcina et al. (2024)).

Table 4.2 presents the reduced and consolidated set of structural requirements, grouped by functional requirement. Although narrowed down, the table retains multiple structural options for some functions. Since the literature did not provide sufficient evidence to determine the best option in each case, the final selection of structural requirements will be determined during the interview phase, described in Section 4.2.

Table 4.2: Mapping potential structural requirements to the functional (sub-)requirements of the tool based on the structural-requirement options derived from the literature, as outlined in Table C.4 in Appendix C.1.

Functional (sub)requirements	Potential structural requirements
The tool includes projected returns of implementing digital technologies in a Twin Transition context.	The tool uses cost-benefit analysis to estimate the financial returns of digital technologies for sustainability (Zhang and Gu, 2021). The tool uses company input on expected gains and costs to create a structured dashboard, supporting scenario testing by modifying input assumptions (Accenture, 2020).

Functional (sub)requirements	Potential structural requirements
The tool allows companies to compare alternative investment paths based on sustainability and cost-effectiveness.	The tool has a prioritization grid using multi-criterion weighting (company-defined) (Macedo et al., 2024).
	It uses TOPSIS to assess proximity to the ideal solutions (e.g. maximum sustainability impact, maximum cost-effectiveness) (Forcina et al., 2024).
	A flowchart is used to identify suitable digital transformation steps based on company goals (Forcina et al., 2024).
	Provides an overview of potential economic and sustainability performance effects (e.g. cost saving and waste recovery) (Xia et al., 2017).
	Uses structured dashboards to visualize comparisons, supporting scenario testing when input assumptions are changed (Accenture, 2020).
The tool enables assessment for various sustainability dimensions for digital technologies used in high-tech manufacturing.	The tool maps impacts across sustainability dimensions and identifies links between them visually (Macedo et al., 2024).
	It integrates sustainability dimensions into an existing model for evaluating non-sustainability objectives (Xia et al., 2017).
	Uses AHP to rank qualitative and quantitative sustainability impacts (Chinoda and Kruger, 2012).
	Splits sustainability maturity into environmental, social and economic axes (Accenture, 2020).
The tool shows both the direct and indirect sustainability impacts of digital tools.	The tool applies LCA to evaluate direct (use-phase) and indirect (procurement and disposal) impacts (Zhang and Gu, 2021).
The tool supports side-by-side comparisons of digital transformation options based on sustainability trade-offs.	AHP is applied to aggregate impacts across multiple sustainability dimensions into composite scores, enabling easy comparison (Chinoda and Kruger, 2012).
The tool links digital transformation efforts to corresponding sustainability goals in a stepwise format.	The tool aligns sustainability and digital maturity phases for stepwise progress (Directorate-General for Internal Market, Industry, Entrepreneurship and SMEs (GROW.D.2), 2022).
	It allows companies to customize roadmaps according to their specific goals (Macedo et al., 2024).
	Defines consecutive steps to guide companies through Twin Transitions (Chinoda and Kruger, 2012).
The tool identifies the resources needed for different implementation dimensions.	The tool assesses the current state, identifies required resources and highlights gaps to desired goals (Huang, 2024).
	Real company input data are used to map digital-resource demand (Accenture, 2020).
The tool allows for different starting points in the Twin Transition pathway depending on maturity.	Multiple standard pathways are selectable based on company goals and maturity levels (Deif, 2011).
	Starting points are defined by combinations of digital and sustainability maturity levels (Shukla and Adil, 2021).
	Defines pathways to guide companies through these maturity stages (Macedo et al., 2024).
The tool is adaptive to the specific context of a Dutch high-tech manufacturing company.	A broad library of digital technologies (varied advancement levels) is available for different company needs (Macedo et al., 2024).
	The tool uses input data (e.g. company size, digital maturity and supply-chain position) to recommend tailored solutions (Alshahrani, 2020).
	Built-in transition phases for the Dutch high-tech manufacturing sector, with options for company-specific customization (Deif, 2011).
	Customizable sections align the tool's output with company preferences (Accenture, 2020).
The tool allows for different paces of transformation, ranging from incremental to radical.	Sustainability steps are adjusted based on digital maturity, allowing gradual or rapid transformation (Huang, 2024).
	Digital and sustainability-maturity progression is flexible, adapting to company preferences (Shukla and Adil, 2021).
The tool provides quantitative KPIs for tracking sustainability progress linked to digital transformation.	The tool defines aggregated KPIs for environmental, social and economic sustainability dimensions (Deif, 2011).

Functional (sub)requirements	Potential structural requirements
The tool supports scenario modeling to explore long-term impacts of different digital strategies.	Structured dashboards are created using company-specific data on costs and gains (Accenture, 2020).
	Scenario-based testing is enabled by modifying input assumptions (Hernández et al., 2016).

4.1.3. Defining contextual requirements based on the intended user

In addition to functional and structural elements, a successful decision-support tool must also consider its context of use, particularly the characteristics, constraints, and working practices of its intended users. These contextual requirements ensure that the tool not only functions as intended in theory but also integrates well into the day-to-day reality of its users’ strategic decision-making processes (Johannesson and Perjons, 2014, p.108-110, 113-116). Contextual requirements differ from functional and structural requirements in that they emphasize the usability, adaptability, and relevance of the tool within the specific environment it is designed for.

This research defines the contextual requirements by first identifying the intended user of the decision-support tool. Since the intended user will ultimately engage with the tool in practice, it is important that their characteristics, usage patterns, and strategic priorities are reflected in the contextual requirements, which focus on how the tool will be used in real-world settings. Once the intended user is clearly defined, their needs can be translated into specific requirements for the tool to ensure it supports their decision-making processes effectively.

The intended user was identified through internal discussions within Accenture Industry X. Given that Industry X operates as an engineering consultancy, and this thesis focuses more on strategic aspects of digital transformation and sustainability performance rather than on the implementation of specific technologies, it was agreed that the most relevant users would be those involved in strategic decision-making, both within Accenture Industry X and on the client side. Based on these internal conversations and an examination of the roles and backgrounds of relevant Accenture Industry X employees and their counterparts in Dutch high-tech manufacturing companies, the intended user profile described below was developed.

Intended user description

The decision-support tool is designed for strategic management roles within high-tech manufacturing companies and technology consulting firms such as Accenture Industry X. These users include C-level executives, managing directors, principal and associate directors, and senior managers responsible for developing strategies to manage the intersection of digital and sustainability transitions in the Dutch high-tech manufacturing sector.

The intended users have expertise in digital transformation, enterprise architecture, and sustainability strategy. They possess deep knowledge of manufacturing operations, supply chains, and the impact of emerging digital technologies, though they do not participate in hands-on technical implementation. Their role involves evaluating large-scale technology solutions, aligning them with business goals, and ensuring they support long-term sustainability objectives. These users typically have more than ten years of experience in consulting or enterprise transformation, supported by advanced degrees in disciplines such as Industrial Engineering, Mechanical Engineering, Computer Science, or Business Administration. Their expertise spans Industry 4.0 technologies, including artificial intelligence, IIoT, cloud computing, and digital twins, and is complemented by an understanding of sustainability frameworks like ESG. Although highly knowledgeable, they often lack structured methods to systematically assess trade-offs and synergies between digital innovation and sustainability targets.

These intended users operate in dynamic environments. They engage in frequent meetings and strategic discussions with C-level stakeholders in Dutch high-tech manufacturing firms, while managing multiple projects simultaneously. The pace of work varies, from long-term strategic planning to rapid technology assessments. While quarterly strategy reviews help refine sustainability roadmaps, many decisions are made under time constraints, often with limited capacity for in-depth technical analysis. As a result, these intended users rely on high-level insights, benchmarks, and best practices to inform their recommendations.

Collaboration with internal experts, such as engineers, technology specialists, and sustainability professionals, is essential to validate proposed solutions. Client engagements typically follow a structured

model, with digital transformation projects spanning 12 to 36 months and implemented in phases. Consultants simultaneously maintain ongoing relationships through quarterly business reviews and technology updates to ensure strategies remain aligned with shifting business and sustainability goals.

In this context, the decision-support tool will offer a structured way to evaluate and prioritize digital technologies based on their sustainability impact. By delivering clear insights, the tool will support the development of more effective Twin Transition strategies.

Contextual requirement definition

Based on the characteristics and workflows of the intended user group, several contextual requirements were identified that must guide the design of the decision-support tool. These requirements reflect the practical conditions under which strategic decisions are made and ensure the tool aligns with users' workflows. For example, the intended user description states how the target users are strategic consultants rather than hands-on engineers, focused on evaluating and communicating the business and sustainability implications of technology, not configuring or implementing it and engaged primarily in client-facing, high-level decision-making with C-level stakeholders.

Therefore, the first requirement is, that the tool should avoid technical implementation-level outputs (like software architecture diagrams, configuration files, or complex engineering models) and should avoid excessive jargon related to the inner workings of AI, IIoT, or cloud systems. Instead, **the tool should present its outputs in a clear and strategic manner, avoiding overly technical language**. This ensures that insights can be immediately understood and communicated in business-oriented discussions, particularly with C-level executives. Clarity in visuals and narrative accessibility are important.

Second, **the tool must support quick analysis cycles**. Given the fast-paced nature of strategy development, users must be able to generate actionable insights within limited timeframes. The tool should synthesize complex assessments into concise, high-level overviews suitable for meetings and short-term evaluations.

Third, **the decision-support tool must produce presentation-ready deliverables**, such as executive summaries, impact visualizations, and strategic KPIs. These outputs should be formatted to seamlessly integrate into decks, reports, and decision memos.

Fourth, given the anticipatory nature of strategic work, **the tool must enable multi-scenario modeling**. Users need to compare different digital investment paths, each with their associated sustainability implications.

Fifth, **the tool must allow for high levels of customization**. Since each company varies in digital maturity, industry segment, and sustainability priorities, the decision-support tool must accommodate these differences to ensure outputs are contextually relevant and trustworthy.

Sixth, **the tool must facilitate cross-disciplinary collaboration**. Strategy development does not occur in isolation; intended users collaborate with engineers, digital architects, and sustainability experts. Therefore, the decision-support tool should include mechanisms that support collaboration across roles.

Seventh, to ensure compatibility with existing work practices, **the decision-support tool must align with recognized standards and frameworks**, such as ESG or CSRD for sustainability. This compatibility minimizes friction during implementation and enhances user confidence.

Eighth, **the tool must support benchmarking capabilities, allowing users to compare digital solutions or sustainability performance against industry standards**. This feature helps contextualize strategic recommendations and provides a reference point for less tangible aspects like social sustainability.

Lastly, **the decision-support tool must be intuitive, with minimal onboarding requirements**. Given the time pressure and multitasking environment in which the intended users operate, the learning curve must be short, and the interface must prioritize usability without sacrificing analytical depth.

4.2. Elicit requirement definition

According to Johannesson and Perjons (2014), the sub-activity "Elicit requirements" follows the artifact outlining phase and focuses on collecting input from stakeholders for requirement formulation.

Interviews are a common method for identifying stakeholder needs (Johannesson and Perjons, 2014). They elicit user preferences by asking participants to suggest features and explicit requirements. Interviews can yield a high volume of relevant input quickly and deepen understanding of stakeholder practices and expectations. However, overly structured interviews may limit creativity, while unstruc-

tured or semi-structured formats often allow richer insights.

This study conducted semi-structured interviews with participants who represent the intended users of the decision-support tool, as described in Section 4.1.3. The purpose of these interviews was three-fold. First, they aimed to refine and prioritize the functional, structural, and contextual requirements identified in earlier stages. Second, the interviews helped adapt the structural and contextual requirements to the specific needs of the Dutch high-tech manufacturing sector. Finally, the interviews also aimed to identify any additional requirements that had not yet been captured but were considered valuable for the tool's design by target users.

4.2.1. Interview design

Format: semi-structured interviews

Before the interview, participants completed a brief survey to evaluate the previously identified functional and structural requirements using the MoSCoW prioritization method. This framework distinguishes between requirements that are essential (Must-have), desirable (Should-have), optional (Could-have), and out of scope (Won't-have or "Will not have right now"). Originally developed for rapid application development projects (Stapleton, 1997), MoSCoW has become a widely adopted method in both software development and project management due to its clarity and practical structure. Compared to abstract prioritization scales such as "high," "medium," or "low," MoSCoW helps stakeholders better understand what each category implies for the design process (Agile Business Consortium, 2014).

The pre-interview survey served two important functions. It introduced participants to the research topic and the specific requirements under consideration, enabling them to think through the material beforehand without being overly scripted or rehearsed. In addition, it enabled more productive use of interview time by focusing discussions on participants' reasoning behind their prioritization, rather than definitions or clarifications. As most participants had demanding schedules, it was important to use the interview time as efficiently as possible. The survey questions are included in Appendix C.2.1.

To ensure consistency while maintaining flexibility across interview sessions, a semi-structured format was used. An interview protocol was developed beforehand to guide the conversations. This protocol outlined key preparatory steps, including how to introduce the research to participants, obtain informed consent, and manage data collection, while ensuring interviews remained aligned with the study's goals. At the same time, it allowed room to adapt the discussion to each participant's expertise and experience.

Each interview followed a general structure, beginning with a conversation about how the participant typically approaches digital or sustainability strategy formulation. This provided context for the tool's practical application and the conditions under which it would be used (the contextual requirements). The conversation then turned to the types of tools the participant currently uses for strategy development. These insights helped clarify which functions or design features are already familiar to the intended users and which they find helpful in existing tools (the structural requirements).

After this contextual grounding, participants were invited to review their completed MoSCoW rankings and were asked to explain their prioritization rationale, especially for the Must-have and Should-have requirements. If time allowed, the discussion also included the Could-have requirements. Finally, the interviews concluded with a segment focused on identifying any additional requirements, functional, structural, or contextual, that participants believed should be included in the tool but were not part of the initial list.

For clarity during discussions, the requirement rankings were shared with each participant during the interview, either by showing them on screen or providing a printed copy. This ensured alignment between the researcher and the interviewee and helped prevent misinterpretations of each requirement.

Participant selection

To ensure that the requirements identified and prioritized in this study were grounded in real-world relevance, interviews were conducted with individuals who closely match the profile of the intended users of the decision-support tool.

The participants were selected using a purposive sampling strategy. This approach was appropriate given the need for targeted expertise and the limited timeframe of the research. In some cases, participants were recruited directly, while others were identified through snowball sampling, where previous participants recommended colleagues with relevant expertise.

In total, five interviews were conducted during this phase. Although this number may seem limited, the participants reflected a diverse cross-section of the high-tech manufacturing domain, as summarized in Table 4.3. They varied in terms of sub-sector focus, depth of involvement in strategic development, and whether their roles were client-facing or focused on advisory and implementation. This diversity ensured that the requirement definitions would not be dominated by a single perspective but reflect a broader range of views and operational realities.

Table 4.3: Anonymized overview of interview participants and their professional background.

Identifier	Sub-sector focus	Strategic involvement	Role orientation	Experience
P1	Client perspective within semiconductor sector	Strategic positioning and proposal development	Client-facing	>12 years experience
P2	Data and strategy within semiconductor manufacturing	Embedding data-driven strategies (incl. sustainability)	Advisory/implementation	± 7 years experience
P3	Client perspective within life sciences and med-tech	Early-stage strategy and transformation support	Client-facing	± 7 years experience
P4	Product-lifecycle management and engineering in high-tech manufacturing and other sectors	Organizational design and tool implementation	Delivery/implementation	15 years experience
P5	Supply-chain and operations in high-tech in general	Process excellence in transformation programs	Advisory/implementation	>5 years experience

4.2.2. Data collection

This research phase involved conducting and transcribing interviews, followed by the initial stages of qualitative data analysis. The interviews were held over the course of approximately one week, between March 27th and April 4th, 2025. Most conversations took place in person, as this setting was considered more conducive to creative and in-depth discussion, particularly when exploring structural requirements that benefit from visual or interactive explanation. When face-to-face meetings were not possible due to scheduling constraints, interviews were conducted via Microsoft Teams. Each session was a one-on-one conversation between the researcher and the participant. All interviews were conducted in Dutch.

All sessions were recorded to facilitate accurate transcription and subsequent analysis. These recordings were automatically transcribed using Microsoft Teams' transcription feature. Although the initial transcripts served as a useful starting point, they required extensive manual correction, particularly in sections involving technical terminology, acronyms, or sector-specific references. This revision process, though time-consuming, was essential to ensure that the data was reliable and accurately reflected what had been said.

Importantly, this manual revision phase marked the initial point of engagement with the data. Although not yet formal coding, this first exposure helped the researcher become familiar with the content and begin identifying patterns and potential directions for the subsequent analysis phase.

4.2.3. Data processing

The primary goal of the interview analysis was to refine and specify the functional, structural, and contextual requirements introduced earlier in Section 4.1. By examining participants' responses in greater depth, this phase also aimed to establish a clear prioritization of these requirements, allowing those deemed most relevant by the intended users to be incorporated into the design of the decision-support tool.

To analyze the qualitative interview data, a thematic analysis approach was applied, following an inductive logic. This means that themes and categories were not predefined but allowed to emerge inductively from the data. This approach was particularly suitable for the exploratory nature of the research, where new types of requirements might surface. The coding process was based on the three-phase structure described by Bhattacharjee (2012), consisting of open coding, axial coding, and selective coding. This structured approach enabled both flexibility in identifying novel themes and consistency in linking the results back to the research objectives.

In the open coding phase, the interview transcripts were analysed using ATLAS.ti. Each transcript was read in detail, and descriptive codes were applied to short excerpts or specific statements that captured a meaningful unit of information. In most cases, individual excerpts were assigned multiple

codes to reflect their layered content. For example, a segment might simultaneously relate to both "adaptability to client context" and "implementation time horizon." These descriptive codes enabled a granular understanding of the issues and ideas brought up by participants and provided the basis for the subsequent stage of the analysis.

Following the open coding, axial coding was applied to begin grouping initial codes into broader, interconnected themes. This phase focused on identifying patterns across the interviews and clustering similar ideas into overarching categories that aligned with the three types of requirements to define. The term "axial" refers to these central categories, around which individual codes are grouped (Sybing, 2025). These themes often required multiple iterations for refinement. For instance, an initial group of codes under the broader theme of "benchmarking" eventually developed into more specific axial codes such as "benchmarking against peers" and "benchmarking internal progress." Similarly, what was initially coded as "awareness" later revealed itself to consist of several dimensions, some of which were more closely related to trade-offs or benchmarking and were therefore reassigned accordingly. To support this phase, a constant comparison method was used. After coding each interview, its results were continuously compared with data from previous interviews. This iterative process ensured that the axial codes were grounded in the full body of data and reflected recurring or contrasting viewpoints across participants (Sybing, 2025).

Finally, in the selective coding phase, the analysis centered on identifying the core themes that directly contributed to the formulation of specific functional, structural, or contextual requirements. At this stage, codes that were most frequently referenced or provided particularly insightful content were synthesized to form the final requirement definitions. A separate collection of quotes and codes was also created for insights that, while not directly tied to a requirement, still offered useful contextual information. Many of these related back to earlier challenges identified in Phase 1. Although this earlier phase is no longer active, retaining these contextual insights could support further development or reflection in later stages of the research or design process.

While independent coding by multiple researchers was not feasible within the scope of this Master's thesis, measures were taken to enhance reliability and validity. After the analysis was completed, the main results were summarized for each interviewee. These summaries were shared with participants for feedback. This step not only helped ensure the accuracy of interpretations but also provided an opportunity for participants to clarify or further elaborate on their statements. This process also ensured that participants' anonymity was preserved while facilitating result verification. The interview summaries can be found in Appendix C.2.3.

Pre-interview survey results

Prior to the interviews, participants completed a survey in which they ranked the identified functional and structural requirements using the MoSCoW prioritization method. Based on these survey responses, a ranking was generated to reflect how participants collectively valued each requirement category. The scores were calculated by assigning weighted values to each priority level: requirements marked as "Must-have" received a score of 4, "Should-have" received a score of 3, "Could-have" was scored at 2, while those rated as "Won't-have" were scored as 1. This ranking produced average normalized scores for each requirement across all participants.

The results reveal a clear difference in perceived importance between functional and structural requirements. Functional requirements generally received higher and more consistent scores, with none being dismissed as unimportant. Structural requirements, by contrast, showed more variation in their rankings, indicating greater variability in how participants perceive the role of tool structure in supporting their decision-making processes. Figure 4.2 displays the average normalized rankings for both types of requirements, with structural requirements on the left and functional requirements on the right.

These findings formed the basis for the interviews themselves, enabling the interviews to focus on participants' reasoning and to refine and enrich the initial set of requirements.

Interview-based requirement definitions

Building on the insights gained from the interviews, a refined list of functional, structural, and contextual requirements was constructed. These definitions emerged from a detailed thematic analysis of the interview transcripts and represent the views and priorities of the intended users of the decision-support tool.

For the functional requirements, a hierarchical structure was identified, distinguishing overarching requirements from more specific sub-requirements. This hierarchy did not apply to the structural or

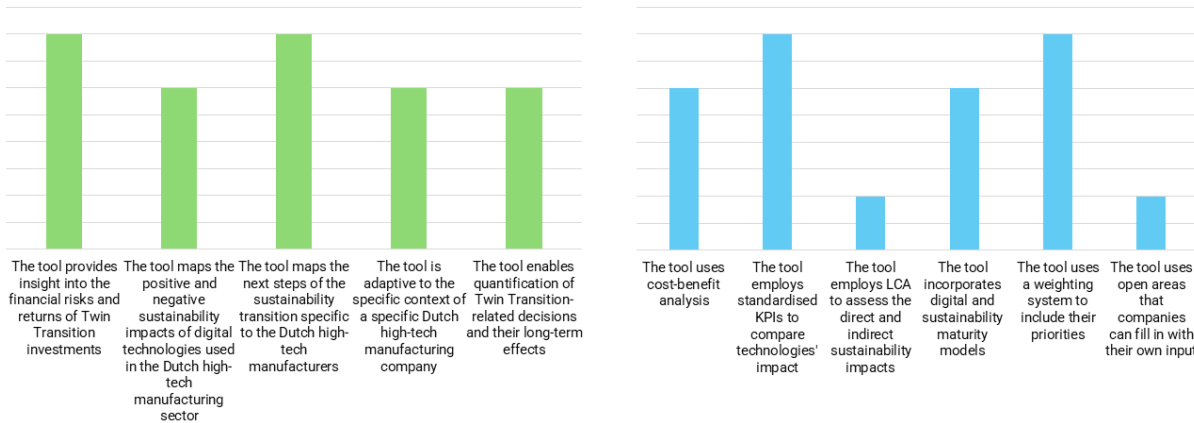


Figure 4.2: Pre-interview survey ranking of functional (on the left) and structural requirements (on the right). Normalized, averaged scores of the MoSCoW framework, showing the relative importance of the identified requirements.

contextual categories, where requirements were treated as stand-alone elements.

Table 4.4 presents the final list of functional requirements, along with their sub-requirements, supporting interview quotes, and the average MoSCoW score assigned by participants. The accompanying quote for each requirement illustrates how it was grounded in stakeholder input. Similar tables were created for the structural and contextual requirements and can be found later in Table 4.5 and Table 4.6 respectively.

A review of the complete requirement set reveals several recurring themes. Across all categories, the emphasis on flexibility, quantification, and strategic relevance was particularly strong. Functional requirements were consistently oriented toward enabling customized, decision-supportive, and value-driven outputs, including elements such as multi-criteria decision analysis (MCDA), return-on-investment calculations, trade-off assessments, and benchmarking mechanisms.

Structural requirements were closely aligned with these functional goals. For example, the ability to quantify digital or sustainability maturity levels was supported by structural preferences for KPI hierarchies and clear visualization methods. The use of MCDA to accommodate varying company priorities further reflects a desire for structured but adaptable tool design.

Contextual requirements relate to who uses it, in what setting, and at which point in the decision-making process, rather than to its features or layout. Because the interviewees represented different roles, working environments, and strategic agendas, no single contextual element was unanimously regarded as a "Must-have". Instead, several items were consistently ranked as "Should-have"s, implying that the tool must remain adaptable to fit each of these different roles.

The few requirements categorized as "Won't-have" were mostly related to reporting and compliance features, such as automatic alignment with frameworks (e.g., CSRD). Participants consistently emphasized that while compliance is important, the primary function of the tool should remain strategic rather than administrative. Including too many compliance-related features was seen as a risk that could dilute the tool's focus and reduce the tool's effectiveness for strategic decision-making.

Table 4.4: Overview of functional requirements for the tool with supporting interview quotes and MoSCoW prioritization.

Main requirement	Sub-requirement	Supporting interview quote	MoSCoW score
The tool is flexible for company specifications	The tool can integrate the priorities of the company in dimensions and suggested actions	P3: "Companies usually select a few Sustainable Development Goals to focus on... So yes, some flexibility is needed."	Must have
	The tool supports progress from different maturity stages in the Twin Transitions	P2: "For example, through a structured approach with milestones... sustainability also isn't something you do just once."	Must have

Main requirement	Sub-requirement	Supporting interview quote	MoSCoW score
	The tool proposes different actions based on company constraints (e.g. budget size)	P1: "When you implement changes in processes or systems, you use the tool to determine: What are my options, and how do I implement them in the most sustainable way?"	Could have
The tool is quantified as much as possible	The tool quantifies maturity stages on which the company can position itself and track quantified progress	P5: "The first thing [the clients] ask is: what's the KPI? How do you make this fact-based?"	Must have
	The tool provides qualitative sidenotes when quantification is not possible	P5: "Some elements can be quantified, others less so, but that's how you get that layering."	Could have
The tool gives insight into the trade-offs associated with the next digital maturity stage	The tool provides the trade-offs between the economic and sustainability dimensions	P2: "If you go left, costs go up but your sustainability score improves. Or the other way around: costs go down, but sustainability drops."	Must have
	The tool provides the trade-offs between the positive and negative sustainability impacts in the different sustainability dimensions	P1: "In my opinion, you need to include both in order to form a well-balanced judgment."	Must have
The tool supports benchmarking to track progress	The tool provides benchmarking of the company's own progress	P1: "That way, they can more objectively assess how their current situation transitions into a future one."	Must have
	The tool provides benchmarking against proxy-peer companies	P2: "It's easy to think internally: we're doing well. But if you then compare to an industry standard, it might turn out you're falling behind."	Should have
The tool supports the business case assessment of progress in the Twin Transitions	The tool supports assessment of the total cost of ownership ROI for 3–5 years	P3: "You're not done with just the initial investment... run-costs, training, licenses... and cloud consumption. You have to take all of that into account for 3–5 years."	Must have
	The tool supports assessing the long-term sustainability benefits in monetary terms (5–10 years)	P5: "When do you consciously invest a bit more money to benefit from it over the next 20 to 30 years?"	Could have
	The tool supports assessing the risk of non-compliance with regulatory frameworks in monetary terms	P3: "For example, look at the risks of fines, lawsuits or other consequences. It just happens if you do nothing."	Could have
The tool gives concrete actions to improve performance		P5: "You're either still completely at the beginning, or already a bit further along. (...) which logical next steps go with that."	Could have
The tool highlights skills needed for the next step in the Twin Transition		P1: "I would keep the tool focused on competencies and not make it too broad... There are other methods for that [referring to skill gaps]."	Could have
The tool supports reporting with relevant sustainability frameworks like the CSRD		P1: "I would really keep compliance separate from the core question: how do I make the best choice when undergoing change?"	Won't have

Table 4.5: Overview of structural requirements for the tool with supporting interview quotes and MoSCoW prioritization.

Requirement	Supporting interview quote	MoSCoW score
The tool conveys a clear core message	P2: "Then you risk analysis paralysis... Clients also often want something that fits their specific situation."	Must have
The tool has clear maturity stages for the Dutch high-tech manufacturing sector	P1: "You really need to be able to compare apples to apples... with a customized matrix."	Must have

Requirement	Supporting interview quote	MoSCoW score
The tool uses MCDA to help companies customize their priorities and view aggregated scores for each sustainability dimension	P2: "You could then say: the E-score goes up, but the S-score drops... That way, you create an average score aligned with their strategic priorities."	Must have
The tool has a KPI hierarchy that starts with a few aggregated KPIs and extends into more detail	P2: "You have primary KPIs... and below those there can be additional KPIs."	Should have
The tool has clear milestones between maturity stages	P2: "For example, through a structured approach with milestones... sustainability also isn't something you do just once."	Should have
The tool makes the scores (current, progress, goal) of each sustainability dimension visible	P5: "I see it as a triangle in which you have to balance three pillars."	Should have
The tool visualizes company status, targets, and benchmarks in a single image	P5: "One picture that captures the entire picture."	Should have
The tool adopts formatting from existing frameworks	P5: "It's the language companies understand."	Could have

Table 4.6: Overview of contextual requirements for the tool with supporting interview quotes and MoSCoW prioritization.

Requirement	Supporting interview quote	MoSCoW score
The tool facilitates strategic discussions on Twin Transition planning	P2: "It's helpful not to show up with a blank page, but with something that shows: this is how we look at it."	Should have
The tool is usable across varying levels of maturity in the Twin Transitions	P5: "You're either still completely at the beginning, or already a bit further along."	Should have
The tool leverages industry best practices to suggest improvements	P2: "We often use best practices from the industry. That is always a good starting point."	Could have
The tool enables rapid decision-making for Twin Transition strategies	P4: "You want to know: I have four alternatives, which one should I choose?"	Could have
The tool enables companies to evaluate different vendor proposals for Twin Transition strategies	P2: "You can license it from us... so they can use it themselves. Then they can apply it internally and determine: who offers me the best digital solution, and what is the sustainability impact of that?"	Could have

4.3. Phase 2 summary

Sub-research question	What functional, structural and contextual requirements must the decision-support tool meet to support the Dutch high-tech manufacturing sector in addressing the identified Twin Transition implementation challenges?
Translation of challenges	•For each of the 4 selected challenges from Phase 1, the challenge was rewritten in a solution-format. •This solution was then translated into a list of functional requirements and sub-requirements.
Structured literature review	•Applied the PRISMA methodology to systematically screen over 600 academic articles; 11 were selected for in-depth analysis. •Identified how literature-based organizational transformation models address similar functional requirements with structural components. •Identified a list of potential structural requirements for the decision-support tool.
Intended user definition	•Identified a profile for the target user of the decision-support tool through internal conversations at Accenture Industry X. •Identified a list of contextual requirements for the decision-support tool
Semi-structured interviews	•Conducted 5 interviews with experts from Dutch high-tech manufacturing that fit the intended user profile. •Ranked the identified functional, structural and contextual requirements with the MoSCoW framework (Must-have, Should-have, Could-have, Won't-have).
Chapter results	Functional requirements: • F1: The tool can integrate the priorities of the company in dimensions and suggested actions. • F2: The tool supports progress from different maturity stages in the Twin Transitions. • F3: The tool quantifies maturity stages on which the company can position itself and track quantified progress. • F4: The tool provides the trade-offs between the economic and sustainability dimensions. • F5: The tool provides the trade-offs between the positive and negative sustainability impacts in the different sustainability dimensions. • F6: The tool provides bench-marking of the company's own progress. • F7: The tool provides bench-marking against proxy-peer companies. • F8: The tool supports assessment of the total cost of ownership ROI for 3-5 years. Structural requirements: • S1: The tool conveys a clear core message. • S2: The tool has clear maturity stages for the Dutch high-tech manufacturing sector. • S3: The tool uses MCDA to help companies customize their priorities and view aggregated scores for each sustainability dimension. • S4: The tool has a KPI hierarchy that starts with a few aggregated KPIs and extends into more detail. • S5: The tool has clear milestones between maturity stages. • S6: The tool makes the scores (current, progress, goal) of each sustainability dimension visible. • S7: The tool visualizes company status, targets, and benchmarks in a single image. Contextual requirements: • C1: The tool facilitates strategic discussions on Twin Transition planning. • C2: The tool is usable across varying levels of maturity in the Twin Transition.

5

Phase 3: Design & development

5.1. From requirements to design idea

After identifying the functional, structural, and contextual requirements in Section 4.2, the design and development of the decision-support tool could begin. The design process started by establishing a structure that would incorporate all the Must-have requirements, address (most of) the Should-have requirements, and allow space for potential inclusion of Could-have requirements, while excluding those that were not necessary. Accordingly, this chapter addresses **sub-research question 3**: *"What is the corresponding decision-support tool that integrates the identified requirements to support Dutch high-tech manufacturing companies in implementing the Twin Transition?"*.

The mapping of the requirements identified in Section 4.2 to the initial outline of the decision-support tool resulted in a three-part structure: a survey to gather company-specific information, a Twin Transition maturity assessment to evaluate the current maturity level, and a next-step overview to recommend digital technologies for improving that maturity. Figure 5.1 shows how these parts are interconnected.

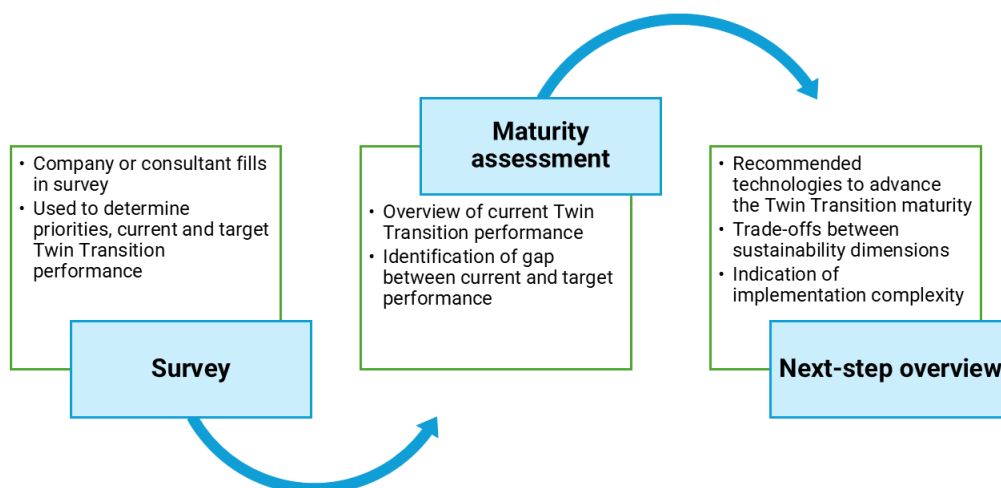


Figure 5.1: Overview of how the three elements of the decision-support tool are interconnected: the survey, the maturity assessment and the next-step overview.

5.1.1. Flow of the decision-support tool elements

The survey: The process begins with a survey to be completed by a Dutch high-tech manufacturing company, or a consultant acting on behalf of a Dutch high-tech manufacturing client. This survey is designed to assess the company's current Twin Transition performance, Twin Transition objectives, and the company's priorities in improving their sustainability goals.

The maturity assessment model: Next, the Twin Transition maturity assessment is presented. In alignment with the requirements from section 4.2, this assessment serves two key purposes: it provides a benchmark for the company's current situation, and it defines clear, sector-specific maturity stages to progress towards the company's Twin Transition target level. The use of a Multi-Criteria Decision Analysis (MCDA) enables the generation of an aggregated score.

The next-step overview: Finally, the tool provides an overview of recommended actions to help the company progress from its current maturity level toward its defined goals. For each suggested digital manufacturing technology, the tool includes recommendations that evaluate both the positive and negative sustainability impacts. It also offers an indication of the complexity involved in implementing each technology.

5.1.2. Match between design and requirements

Table 5.1 illustrates how this structure accommodates all the requirements outlined in Section 4.2. It ensures that the tool meets all the 'Must-have' criteria while leaving room for 'Should-have' and potential 'Could-have' elements. Additionally, this structure supports strategic decision-making (a contextual 'Should-have' requirement), as it provides users with a clear understanding of their current position and the areas they can improve. This enables them to make well-informed decisions on how to improve their sustainability strategy, integrating both digital and sustainable transition goals.

Table 5.1: Overview of how the three decision-support tool elements address the Must-have and Should-have requirements identified in Section 4.3.

Decision-support tool element	Requirement	How it is addressed
Survey	Integrate priorities from the company (F1) & MCDA to customize priorities (S3)	In the survey, users provide their priorities and goals. The aggregated Twin Transition maturity score is then calculated using the importance weightings that the user specifies for each sustainability dimension.
	Supports progress from different maturity stages (F2, C2)	The survey allows users to indicate the current maturity level of their company in the Twin Transition process. This information is then used to suggest appropriate next steps later in the tool.
	Benchmarking of company's own progress (F6)	Based on the responses in the survey, the tool visualizes the company's current status and tracks progress toward the company's sustainability goals.
Maturity assessment model	Integrate priorities from the company (F1) & MCDA to customize priorities (S3)	The maturity assessment model uses the data from the survey and applies the MCDA approach to calculate aggregated maturity scores based on the importance weightings provided by the user.
	Supports progress from different maturity stages (F2, C2) & clear milestones between maturity stages (S2, S5)	The maturity assessment model includes multiple stages, allowing companies to assess their current position, whether they are at a low or high maturity level, and plan for progress accordingly.
	Quantifies maturity stages for positioning and tracking (F3) & clear maturity stages (S2, S5, S7)	The maturity model includes distinct levels, each with defined characteristics. This structure makes it easy to track which maturity level the company is in and provides a clear roadmap for progress.
	Benchmarking of company's own progress (F6) & clear core message (S1, S7) & clear KPI hierarchy (S4) & current score vs goal is visible (S6)	The maturity model visually indicates the company's current maturity level and compares it with the company's target level, making the gap between current status and goals clear. The tool also breaks down aggregated scores into more detailed measures for better tracking.
	Benchmarking of company's progress against proxy-peer companies (F7)	The maturity model highlights the company's position in comparison to similar companies, such as the average Dutch high-tech manufacturing company, allowing for benchmarking against peers.
Next steps overview	Integrate priorities from the company (F1)	The Twin Transition priorities identified in the survey will be factored into the recommended next steps, focusing on areas where improvement is most needed.

Decision-support tool element	Requirement	How it is addressed
	Shows trade-off between economic and sustainability dimensions (F4)	The recommended digital manufacturing technologies to improve the sustainability impacts will include a cost-benefit analysis that compares the economic impact with sustainability outcomes, helping the company understand the trade-offs.
	Shows trade-off between positive and negative sustainability impacts (F5)	The suggestions will highlight the positive and negative sustainability impacts, providing a balanced view of how different actions affect various sustainability dimensions.
	Assesses total cost of ownership ROI for 3–5 years (F8)	The tool will provide an assessment of the total cost of ownership, showing the return on investment over a 3–5 year period to help companies make informed decisions.

Design approach overview

This structure consists of three interdependent components that need to be developed: the survey, the maturity assessment, and the next-step overview. While each requires its own design approach, they are closely linked. Development begins with the maturity assessment, since its outcomes determine which dimensions, maturity levels, and KPIs must be included. Once these are defined, the survey can be developed to collect the necessary data from companies, and the next steps can be determined accordingly.

5.2. Developing a Twin Transition maturity model for the Dutch high-tech manufacturing sector

In line with the Design Science Research methodology (Johannesson and Perjons, 2014), the development of the maturity model should be based on existing frameworks. According to this methodology, “The results of the activity should always be based on and related to existing work.” This ensures that requirements and artifacts are not developed in isolation but instead are contextualized within prior research. This approach helps stakeholders and researchers assess the significance of the proposed solution by clearly showing how it builds upon, diverges from, or improves existing work (Johannesson and Perjons, 2014, p. 112).

Therefore, the first step in this research was to review existing models that could serve as the foundation for the Twin Transition maturity model, specifically tailored to the Dutch high-tech manufacturing sector.

5.2.1. Selection of a suitable maturity model as a foundation

As discussed in Chapter 1, no existing Twin Transition maturity models are directly applicable to the Dutch high-tech manufacturing sector. The few available Twin Transition models that incorporate a maturity framework are too limited in scope to serve as a foundation for this case. At the time of this research, only two such models were identified: the model developed by Meuser et al. (2024) and the model proposed by Breiter et al. (2024).

Rationale for choosing a sustainability maturity model

The model by Meuser et al. (2024) aims to support industrial decarbonization within the Twin Transition by offering a maturity assessment spanning strategic, tactical, and operational levels. However, this model is difficult to adapt for the specific context of the Dutch high-tech manufacturing sector. Its thematic scope is so narrow that virtually none of its dimensions align with the requirements defined in Section 4.2. Furthermore, because the model operates across strategic, tactical, and operational levels, it lacks the necessary detail to adequately distinguish the ways in which digital technologies support sustainability outcomes, which is a central functionality in this research.

On the other hand, the model by Breiter et al. (2024) presents a capability-focused approach to the Twin Transition and is positioned as being applicable across many organizations. Despite its broad applicability, this model also falls short as a foundational framework for the purposes of this research. The main reason is that this study is not limited to assessing organizational capabilities alone, but also emphasizes how digital technologies themselves are used to enhance sustainability performance. Since the model by Breiter et al. (2024) does not address this intersection in sufficient detail, it is not suitable for adaptation.

Given the lack of appropriate Twin Transition maturity models, the choice was narrowed to either a digital transformation model or a sustainability performance model. As the essence of the Twin Transition lies in using digital technologies to drive improvements in sustainability performance (Hellemans and Oostervink, 2025), it was logical to select a sustainability maturity model as the conceptual foundation for this research.

Rationale for selecting a practice-based model

Once the sustainability maturity model perspective was chosen, the next decision was whether to base the foundation on an academic model or a practice-based one. An academic model was ultimately not selected due to its limited alignment with the practical and industry-specific objectives of the decision-support tool, which is intended for stakeholders in the Dutch high-tech manufacturing sector. As discussed in Section 4.1.3, the tool must deliver actionable, context-sensitive insights to guide decision-making during digital and sustainability transitions.

The academic sustainability models reviewed in Chapter 1 tend to be theoretical and generic in nature. They generally lack the adaptability and sector-specific detail needed to address the diverse and complex needs of companies within the Dutch high-tech manufacturing sector. In contrast, a practice-based maturity model is better suited to meet these needs. Such models offer more directly applicable insights, are grounded in real-world organizational dynamics, and facilitate the development of concrete next steps for decision-making. For these reasons, a company-developed model was seen as more appropriate within the user-centered framework of this Design Science Research study, and is better aligned with the contextual requirements outlined in Section 4.1.3.

There are very few sustainability maturity models from companies, public institutions, or consultancies that are publicly available. Given that this research was conducted as part of an internship at Accenture, the researcher had access to multiple internally developed sustainability maturity models. This accessibility, combined with the practical advantages of a consultancy-based model, led to the decision to select an Accenture sustainability maturity model as the foundation for this research.

It is acknowledged that relying on a proprietary model developed by a specific consultancy may reduce the generalizability of the resulting decision-support tool. Organizations not affiliated with the consultancy company might be less inclined to adopt the model or view it as neutral. Nevertheless, the trade-off was considered acceptable because of the need for an actionable and sector-specific model. The contextual requirements and availability of Accenture's materials justified this choice despite the potential limitations in broader appeal.

The chosen foundation model: Accenture Industry Sustainability Maturity Model

After a comparative evaluation of available models, the Accenture Industry Sustainability Maturity Model was selected as the most appropriate foundation for developing the Twin Transition maturity model for the Dutch high-tech manufacturing sector. This model is designed to assess ESG-related sustainability performance across a wide range of industrial departments, including research and development, manufacturing processes, and supply chain management.

The inclusion of the manufacturing process as a specific dimension made this model particularly suitable for adaptation to the Dutch high-tech manufacturing context. Additionally, it aligns well with the decision-support tool's functional requirements and supports the strategic decision-making processes of its intended users. Table D.1 in Appendix D.1 outlines the degree to which the Accenture Industry Sustainability Maturity Model fulfills the requirements of the tool identified in Section 4.2.

With the selection of a foundation model, the next step is to review and adapt the Accenture Industry Sustainability Maturity Model to fit the specific demands of the Twin Transition within the Dutch high-tech manufacturing sector. As shown in Table D.1, the model already aligns closely with many of the identified requirements, particularly the structural and contextual ones. However, to fully serve as a Twin Transition maturity model in this specific setting, several aspects will require targeted adaptation.

5.2.2. Structured approach for reviewing and adapting the foundational model

To ensure that the Accenture Industry Sustainability Maturity Model can effectively serve as the foundation for a Twin Transition maturity model tailored to the Dutch high-tech manufacturing sector, review and adaptation of each element is necessary. Each component of the model is critically examined and, where needed, adjusted to meet the requirements defined in earlier phases of this research. To guide this process in a structured and academically grounded way, a recognized maturity model development

method is applied. By aligning the adaptation with each step of this method, evaluating whether the existing model meets the necessary criteria or requires refinement, the resulting model will be both academically robust and practically relevant for its intended context.

The framework proposed by De Bruin et al. (2005) serves as the methodological basis for this structured approach. This framework is particularly suited for the purpose of this study, which aims to integrate both digital and sustainability transformations, rather than addressing these domains in isolation. The framework by De Bruin et al. (2005) consists of six development stages. The first step, Scope, which defines the focus of the model, was already completed in Phase 1 of the Design Science Research (DSR) process, where the main challenges were identified. The second step, Design, establishes the model's structure and was addressed in Phase 2 through the formulation of design specifications in the form of requirements. The third step, Populate, focuses on creating the model's content and forms the central task of the current phase. The fourth step, Test, will be implemented in Phase 4 through case-based evaluation to ensure relevance and rigor. The fifth step, Deploy, will be achieved through the publication of this thesis, and the final step, Maintain, lies beyond the scope of this study.

The current focus, the Populate phase, consists of three key sub-steps that together form a structured approach to develop the model's content:

1. **Dimension selection:** In this initial step, the main dimensions and corresponding sub-dimensions of the maturity model are defined. These represent the broad thematic areas and specific components that the model will assess.
2. **Level establishment:** This step involves defining the maturity levels of the model in a top-down manner. These levels typically represent cumulative stages of development, with five levels being most common. Each level is assigned a short, meaningful name and is characterized by a set of defining features that indicate increasing sophistication and alignment with goals.
3. **Indicator identification:** Once the dimensions and maturity levels are established, measurable indicators are developed to assess progress within each (sub-)dimension. These indicators provide observable criteria that reflect the level of maturity and enable structured evaluation across the model's components.

These three sub-steps from De Bruin et al. (2005) offer a structured path for adapting the Accenture Industry Sustainability Maturity Model to the context of the Dutch high-tech manufacturing sector. Following this approach, the adaptation process will begin by reviewing and refining the model's dimensions and sub-dimensions. It will then proceed with the definition of maturity levels and conclude with the identification of relevant indicators. This method ensures the resulting Twin Transition maturity model is both academically grounded and tailored to the needs of its intended users.

5.2.3. Dimensions: review and adaptation

According to the method developed by De Bruin et al. (2005), the development of a maturity model begins with identifying and defining its main dimensions. In the Accenture Industry Sustainability Maturity Model, two main types of dimensions are distinguished: sustainability dimensions and implementation dimensions.

Sustainability dimension review

The sustainability dimensions in the Accenture model are based on the widely recognized ESG framework, which stands for Environment, Social, and Governance. ESG is an established standard in corporate sustainability communication and provides a comprehensive structure for evaluating the environmental impact, social responsibility, and governance practices of an organization (Sklarew, 2023).

For the purposes of this research, the ESG framework appears to be a strong fit for the Twin Transition maturity model tailored to the Dutch high-tech manufacturing sector. Insights gathered during interviews, as outlined in Sections 3.2 and 4.2, indicate that the intended users are already familiar with ESG. In fact, multiple interviewees referred to ESG without being prompted by the researcher, suggesting not only familiarity but also a degree of comfort in using the framework. This is further supported by the fact that several Dutch high-tech manufacturing companies already use ESG in their communication and reporting on sustainability performance (ASML Holding N.V., 2025b; Koninklijke Philips N.V., 2025; Thales Group, 2021). Given this existing familiarity and usage, ESG provides a logical and user-aligned foundation for the sustainability side of the Twin Transition maturity model.

Implementation dimension review

In terms of implementation, the Accenture model outlines five key dimensions: People, Process, Policy, Technology, and Data. Each of these captures a different aspect of how maturity initiatives are embedded within an organization. The People dimension refers to the employees at all levels in an organization and it encompasses their skills, motivation, engagement and responsibilities. The Process dimension focuses on improving operational workflows to enhance flexibility and scalability. Policy concerns the creation of formal governance structures and strategic frameworks, that set the boundaries within processes operate. Technology is centered on adopting advanced tools to support innovation and operational excellence. Finally, the Data dimension supports informed decision-making by driving both technological applications and process optimization.

This Accenture framework seems to be a good fit with the dimensions for the digital transformation side of the Twin Transition maturity model for the Dutch high-tech manufacturing sector. These implementation dimensions align well with several academic models that examine organizational transformation, as referenced in Section 4.1.2. For instance, the Decision Support System (DSS) framework by Hernández et al. (2016) includes constructs such as ‘people competences’ (which parallels the People dimension), ‘operations management’ (aligned with Process), and ‘DSS architecture’ (aligned with Technology). Similarly, the Climate Change Response Ladder by Chinoda and Kruger (2012) features dimensions that correspond with People, Process, Policy, and Technology. This alignment with academic literature reinforces the validity of the Accenture implementation dimensions as a solid foundation for the digital transformation component of the Twin Transition maturity model.

However, a closer examination reveals that not all five dimensions from the Accenture model equally fit within the components of the decision-support tool. Specifically, the People, Process, and Policy dimensions align well with both the maturity component and the next-steps component of the decision-support tool. In contrast, the technology and data dimensions do not fit as separate maturity areas within the tool when there is also a next-steps component. This is because, under the Twin Transition maturity framework, Technology and Data are integrated elements: they are embedded within the maturity assessment itself and are not intended to be assessed as standalone dimensions. Moreover, according to the EU’s definition of the Twin Transition, technology and data are regarded as enablers, tools that support transformation, rather than goals in themselves. Consequently, maximizing maturity specifically within these dimensions is not meaningful for the Twin Transition, as their role is instrumental rather than outcome-focused.

Therefore, when selecting dimensions for the decision-support tool from the organizational transformation implementation perspective, the final choice is to include People, Process, and Policy. These dimensions effectively capture the important areas of maturity and strategic implementation while recognizing technology and data as embedded enablers rather than separate maturity targets.

Selected dimensions and their interaction

Based on this reasoning, the dimensions selected for the Twin Transition maturity model are the ESG sustainability dimensions and the People, Process, and Policy (PPP) implementation dimensions. The ESG dimensions provide a strong foundation for assessing sustainability performance, while the PPP dimensions offer an appropriate structure for evaluating digital transformation maturity. Together, these dimensions reflect the dual focus of the Twin Transition.

However, the original Accenture Industry Sustainability Maturity Model does not specify how these dimensions interact. Since the Twin Transition maturity model for the Dutch high-tech manufacturing sector requires a coherent integration of the ESG and PPP dimensions, their interaction must be defined explicitly. This interaction has been determined based on the definitions and roles of the respective dimensions, as described above. An overview of how the ESG and PPP dimensions are integrated to enable a unified Twin Transition maturity assessment is presented in Table 5.2.

Table 5.2: Connection between ESG dimensions and the People, Process, and Policy dimensions

ESG dimension	Dimension	Connection
Environmental (E)	People	Employees gain increasing skills and knowledge in managing energy, emissions, waste, and resource use. Roles evolve from awareness to oversight of optimizing environmental systems.

ESG dimension	Dimension	Connection
Social (S)	Process	Operational activities are structured to monitor, control, and continuously improve the use and impact on environmental resources. Efficiency and environmental sustainability are built into workflows and decision-making.
	Policy	Environmental policies define how the organization manages its environmental responsibilities, sets measurable goals, and ensures accountability for performance and compliance.
	People	Employees are supported through inclusion, safety, well-being, and learning initiatives. Capabilities grow through training, and individuals contribute to a more equitable and healthy workplace.
	Process	Workflows and routines are designed to promote health, safety, equity, and personal development. Operations account for human needs, fair treatment, and participation.
	Policy	Social policies set out commitments to diversity, equity, safety, well-being, and human rights, ensuring these principles are embedded across the organization's practices.
Governance (G)	People	Employees understand ethical standards and are empowered to report concerns and act with integrity. Ethical behavior is encouraged, reinforced, and aligned with organizational values.
	Process	Governance processes ensure transparency, accountability, and compliance. Oversight mechanisms are in place to manage risk, prevent misconduct, and uphold ethical standards.
	Policy	Governance policies define the rules, structures, and responsibilities for decision-making, risk management, and ethical conduct within the organization.

5.2.4. Review and selection of sub-dimensions

Following the next step in the maturity model development method by De Bruin et al. (2005), the sub-dimensions of the Accenture Industry Sustainability Maturity Model are reviewed after the main dimensions have been established. While the model does not distinguish sub-dimensions within the PPP implementation dimensions, it does provide sub-categories within the ESG sustainability dimensions. These sub-categories can therefore be considered the sub-dimensions of the maturity model.

In the environmental domain, the model includes emissions, water, environmental stewardship, resource use, environmental management, environmental solutions, and waste. For social sustainability, it distinguishes product quality and safety, compensation, employment quality, labor practices, community relations, product access, human rights, training and development, diversity, and occupational health and safety. In the governance category, the model identifies business ethics, transparency, and corporate governance.

However, it cannot be assumed that all of these sub-dimensions are equally relevant to the Dutch high-tech manufacturing sector, or that no other sustainability impacts are relevant. The original Accenture model addresses a broad range of industrial activities, including research and development, supply chain management, and marketing and sales. As a result, it likely includes ESG impacts that are not specific to the manufacturing process itself and should therefore be excluded. Additionally, the model was designed for general industrial use and does not account for the unique characteristics of the Dutch high-tech manufacturing sector, as described in Chapter 1 and Appendix A.

To identify the most relevant ESG sub-dimensions for the Dutch high-tech manufacturing context, it was necessary to perform a targeted review. Interviews with experts from this sector, as detailed in Section 3.2, revealed that regulation is the primary driver for sustainability performance improvement. For instance, interviewee M2 highlighted European regulations as a major influence, particularly for large, internationally operating firms. As a result, the sub-dimensions selected for the decision-support tool must align with regulatory expectations. The EU's Corporate Sustainability Reporting Directive (CSRD) was identified in multiple interviews as the key regulatory framework influencing sustainability efforts within the sector. The goal is not to develop the tool as a reporting instrument (as stated in the requirements in Section 4.2), but rather to ensure that it aligns with the company's sustainability priorities. While the input to the tool (namely, the sustainability sub-dimensions) should therefore be consistent with relevant legislation, the tool's output is not intended to serve as formal reporting.

Based on this insight, the European Sustainability Reporting Standards (ESRS), which are the stan-

dards that underpin the CSRD, were reviewed to determine which standards are most applicable to Dutch high-tech manufacturing operations. This ensures that the selected sustainability impacts are not only relevant but also compliant with regulatory requirements and therefore align with the priorities of Dutch high-tech manufacturing companies.

Review of the ESRS

The review process began by identifying all ESRS standards potentially relevant to high-tech manufacturing activities. This was done in parallel with a review of the sector-specific operational definitions, as outlined in Chapter 1. Importantly, the ESRS are already structured according to the ESG categories, which aligns well with the sustainability dimensions selected for the Twin Transition maturity model. This predefined categorization supports a clear and consistent connection between regulatory standards and the maturity model's structure. A full analysis of these impacts is provided in Section D.2.1.

After identifying relevant ESRS standards, the significance of the associated sustainability impacts for the Dutch high-tech manufacturing sector was assessed. To quantify the relevance of environmental impacts, Environmentally Extended Input-Output Analysis (EEIOA) was applied. EEIOA is particularly suitable in this context because it allows for the estimation of environmental impacts, such as emissions, resource use, and waste generation, on a sectoral level. This helps determine whether the environmental impacts listed in the ESRS are actually significant for the Dutch high-tech manufacturing sector in its entirety in terms of scale and intensity. For instance, if a certain pollutant is required to be reported under ESRS, EEIOA helps assess whether the Dutch high-tech manufacturing sector emits that pollutant specifically in substantial quantities or only in negligible amounts. This ensures that only the most relevant and material environmental indicators are retained in the final decision-support tool.

For environmental impacts that could not be quantified through EEIOA, due to a lack of data, a qualitative review was conducted. For the social and governance dimensions, the MSCI ESG Industry Materiality Map was used to assess which topics are most important to sectors related to high-tech manufacturing. This tool is designed to identify ESG risks and opportunities that are financially material across different industries (MSCI Inc., 2023a). It incorporates the Sustainability Accounting Standards Board (SASB) Materiality Map, ensuring consistency with internationally accepted sustainability reporting frameworks (MSCI Inc., 2023b). Using the MSCI ESG Industry Materiality Map is appropriate in this context because it highlights the ESG topics that are most likely to impact financial performance and operational resilience in high-tech sectors. This aligns with the objectives of the decision-support tool, which aim to support companies in prioritizing sustainability efforts that are not only sustainability-relevant but also strategically and financially significant. By relying on this map, the social and governance impacts selected for the model are well-grounded in both materiality assessments and sector-specific relevance.

EEIOA for selecting relevant quantifiable environmental impacts

Environmentally Extended Input-Output Analysis (EEIOA) is a method used to assess the environmental impacts of economic activities at the sectoral or economy-wide level. It builds on traditional input-output analysis by integrating environmental data, which enables a detailed assessment of how production and consumption contribute to environmental pressures, including those embedded in supply chains.

A detailed explanation of the EEIOA method used is provided in Section 2.3.3. The full set of results, is provided in Section D.2.2. A summary of the relevance assessment of ESRS environmental impacts, based on EEIOA, is included in Table 5.3.

Selecting relevant non-quantified environmental impacts

The environmental impacts not included in EXIOBASE for ESRS E2-5 (use of hazardous substances), ESRS E4-5 (biodiversity and ecosystems) and ESRS E5-5 (waste management and circularity) were assessed through qualitative review of (grey) literature specific to the Dutch high-tech manufacturing sector. Appendix D.2.3 provides the in-depth analysis and conclusions, whereas the conclusions for each of these three impacts is included in Table 5.3.

Selecting relevant social and governance impacts with the MSCI ESG Industry Materiality Map

For ESRS standards that could not be evaluated using EEIOA, mainly those related to social and governance impacts, the MSCI ESG Industry Materiality Map was used to assess their relevance to the Dutch

high-tech manufacturing sector, as defined in Chapter 1.

This assessment involved aligning each ESRs social and governance standard with corresponding categories in the MSCI ESG map. The high-tech manufacturing subsectors identified in the (Velthuisen et al., 2024) report were matched to related industry subsectors in the MSCI map. Each matched category in the MSCI map carries a materiality weight, which reflects the relative importance of that ESG issue for the given sector. To determine the overall importance of each ESRs standard for the Dutch high-tech sector, the MSCI weights were multiplied by the sub sector weights from the Velthuisen et al. (2024) report. This approach allowed for a weighted evaluation of relevance, taking into account both the materiality of each ESG issue and the structure of the high-tech industry. A more detailed explanation of this method is provided in Appendix D.2.4. A summary of the MSCI ESG Industry Materiality Map assessment on the relevance of ESRs impact categories for the Dutch high-tech manufacturing sector is included in Table 5.3.

It is important to note that the results presented in Table D.5 apply to the high-tech manufacturing sector in general, rather than specifically to the Dutch high-tech manufacturing sector. To the best of the researcher's knowledge, no ESG-weighting models currently exist for the Dutch high-tech or its subsectors. Therefore, all impacts deemed relevant to the high-tech manufacturing sector in general were applied to the Dutch high-tech manufacturing sector during the first design cycle.

Table 5.3: Summary of importance review of ESRs impacts for the Dutch high-tech manufacturing sector.

Assessment method	ESRS impact	EEIOA evaluation
EEIOA	E1-5 Energy consumption & energy mix	EEIOA shows that the Dutch high-tech manufacturing sector was among the top 5 energy consumers in 2020, using ~20,680 TJ. While direct energy use is only 2% of total embodied energy, it remains nationally significant. Most energy use is electricity, making it dependent on the national energy mix.
EEIOA	E1-6 Greenhouse gas emissions	The sector is a major emitter of greenhouse gases. HFCs are the most significant Scope 1 emissions, followed by CO ₂ and PFCs. Methane also contributes notably, while emissions of SF ₆ remain relatively low and nitrogen trifluoride emissions are virtually zero.
EEIOA	E2-4 Air, water and soil pollution	The sector emits low levels of NOx and particulate matter, but relatively high levels of SOx and NMVOCs. It has no direct nitrogen or phosphorus soil emissions; such emissions are embedded in the supply chain.
Literature	E2-5 Hazardous substance & chemical use	Although the Dutch high-tech manufacturing sector handles a relatively low volume of materials, it relies heavily on highly toxic and specialized chemicals. This results in significant environmental risks from chemical waste.
EEIOA	E3-4 Water use & waste water management	The sector uses ~7 times less direct water than the average Dutch manufacturing sector. Direct use is just 2% of its total water footprint. Water use is stable, reflecting efficient management.
Literature	E4-5 Biodiversity impact	High-tech manufacturing factories are often near sensitive ecological areas, contributing to biodiversity pressures through land-use conflict and nitrogen emissions, though other impacts like soil, noise, and light pollution are generally well-managed and less significant. Therefore, this impact is not seen as highly relevant for the Dutch high-tech manufacturing sector.
EEIOA	E5-4 Resource consumption	The sector uses no raw materials directly, only pre-processed inputs. It relies heavily on critical materials (e.g., rare earths), which are embedded in its supply chain.
Literature	E5-5 Waste management & circularity	While the sector is advancing circular economy strategies, most sub-sectors remain in a transitional phase, with ambitious goals but current practices still falling short of ESRs E5-5 targets.
MSCI ESG Industry Materiality Map	S1-8 Engagement & representation	Of high importance for specifically the high-tech manufacturing sector according to the MSCI review.
EEIOA & MSCI ESG Industry Materiality Map	S1-9 Diversity & inclusion	EEIOA shows a modest rise in female participation between 2012–2022. Women represent a higher share of headcount than total hours worked, indicating part-time work. Disability data not assessed with EEIOA. Of high importance for specifically the high-tech manufacturing sector according to the MSCI review.
MSCI ESG Industry Materiality Map	S1-10 Fair wages & working conditions	Not an area of importance for specifically the high-tech manufacturing sector according to the MSCI review.

Assessment method	ESRS impact	EEIOA evaluation
MSCI ESG Industry Materiality Map	S1-13 Training & skills	Of high importance for specifically the high-tech manufacturing sector according to the MSCI review.
MSCI ESG Industry Materiality Map	S1-14 Occupational health & safety	Of medium importance for specifically the high-tech manufacturing sector according to the MSCI review.
MSCI ESG Industry Materiality Map	S1-15 Work-life balance	Of small importance for specifically the high-tech manufacturing sector according to the MSCI review.
MSCI ESG Industry Materiality Map	S1-16 Equal pay & benefits	Not an area of importance for specifically the high-tech manufacturing sector according to the MSCI review.
MSCI ESG Industry Materiality Map	G1-1 Ethical culture & behavior	Highly important across all high-tech manufacturing sub sectors according to the MSCI review.

Final selection of relevant ESG sub-dimensions in the Twin Transition context

Now that the relevant ESG sub-dimensions have been identified using ESRS categories, EEIOA, qualitative review, and the MSCI ESG Industry Materiality Map, a final selection must be made. This selection focuses on those sustainability dimensions that can be improved using digital technologies. Since the goal of the decision-support tool, and therefore the Twin Transition maturity model, is to show how digital tools can help improve sustainability performance, only ESG impacts that can be addressed with digital technologies are included. If a digital solution cannot contribute to solving a specific ESG issue, that issue falls outside the scope of the Twin Transition model.

This section reviews how digital technologies used in the Dutch high-tech manufacturing sector can support improvements in the ESG performance of the identified sub-dimensions. To determine which technologies are relevant, three steps were followed. First, digital technologies currently used in digitalization and transformation of manufacturing processes in the Dutch high-tech sector were identified. Then, based on literature, it was assessed whether and how these technologies could support improvement in one or more of the ESG sub-dimensions. Finally, interviews were conducted to confirm the findings from the literature and to identify any missing links where needed.

Identification of digital technologies for high-tech manufacturing processes

Internal documentation from Accenture on digital manufacturing technologies served as a starting point. From this, technologies that apply specifically to the manufacturing process were selected. Technologies meant for other departments (such as laboratory information management systems (LIMS) used in R&D) or technologies that connect departments (like product lifecycle management (PLM)) were excluded. This is because the focus of the decision-support tool is limited to the manufacturing process itself.

In addition, technologies were excluded if they did not match the definition of digital manufacturing technologies used in this research, as outlined in Chapter 1. This definition includes digital systems that manage, monitor, and optimize production processes, with a focus on data flow, control, automation, and connectivity. For example, Accenture's documentation includes Smart Quality Management, but this is not a core technology. It is a business application built from other technologies such as MES, SPC, sensors, and analytics. Since the goal here is to identify core digital technologies with potential to improve sustainability impacts, such composite business applications are not included. The full list of technologies identified from Accenture's internal documentation is shown in Table D.6 in Appendix D.2.5. This table outlines each technology, its application, and the reason for inclusion or exclusion where applicable.

Accenture's documentation was a strong foundation, as the listed technologies are actively used in real high-tech manufacturing environments. However, to address potential bias and to ensure completeness, academic literature was also reviewed. This was done to identify any additional digital technologies relevant to high-tech manufacturing that may not have been included in the Accenture list.

A structured academic literature search was carried out using two major databases: Scopus and Web of Science. The rationale for choosing these databases is explained in Section 2.3.1. Search

terms were developed to cover two main areas: digital technologies (Term Type 1) and the high-tech manufacturing process (Term Type 2). The search terms used are listed in Table 5.4. Boolean operators were applied during the search. Within each term group, "OR" was used (e.g., "Industry 4.0" OR "I4.0"), while "AND" was used to connect different groups (e.g., "Industry 4.0" AND "High-tech manufactur*"). The search identified 26 research articles from Scopus and 61 from Web of Science. Both searches were conducted on May 6th, 2025. Two more relevant papers were identified through snowballing.

Table 5.4: Search terms used for the structured review to identify digital technologies relevant to the high-tech manufacturing process.

Term type 1	Term type 2
Industry 4.0	High-tech manufactur*
I4.0	High technology manufactur*
Smart manufactur*	Advanced technology manufactur*
Digital manufactur*	

The screening phase filtered out irrelevant articles by applying clear criteria to the titles, abstracts, and keywords. Only articles that were accessible in full text through university or Accenture resources were included. Papers had to be written in English. Bibliometric reviews were excluded, as they focus on publication trends rather than identifying specific digital tools. After applying these criteria, the number of relevant papers was reduced to 61. After removing duplicates, 37 articles remained for further review.

In the eligibility phase, more detailed content criteria were applied to further narrow down the selection. The papers were checked to confirm whether they proposed digital technologies not already in the Accenture list, whether the technologies were applicable to high-tech manufacturing, and whether they applied specifically to the manufacturing process. This reduced the number of papers to 9. A second round of review was then carried out using the full text of the remaining articles. The same criteria were applied. In the end, none of the articles proposed technologies that met the definition of digital manufacturing used in this research.

For example, 3D printing, as discussed by Yuan (2020), was excluded. Although it enables digital workflows, it is itself a production method rather than a digital technology that manages, monitors, or optimizes production. Similarly, blockchain, as proposed in Li et al. (2025), was excluded because it does not operate in real-time production environments. While blockchain supports secure and traceable data sharing, it is not directly involved in managing or optimizing the shop floor.

As a result, no academic sources added technologies beyond those already identified in the Accenture documentation. Therefore, the list of digital manufacturing technologies included in this study is considered complete at the time of the research. Table 5.5 provides an overview of the selected technologies and their roles within the high-tech manufacturing process.

Table 5.5: Overview of selected digital manufacturing technologies and their applications in (high-tech) manufacturing companies.

Digital technology	What it is	Application in (high-tech) manufacturing companies
ERP (enterprise resource planning)	Central software to manage finance, inventory, procurement, etc. all related to executing production	Integration of data across departments to streamline the operational and transactional aspects of manufacturing.
APS (advanced planning and scheduling)	Production planning, scheduling	Optimization of production schedules, efficiency through scenarios.
MES (manufacturing execution system)	Software managing/monitoring production processes on the shop floor in real time	Track production, integrates with ERP, ensures quality.
SCADA (supervisory control and data acquisition)	System for real-time monitoring (sensors/devices)	Overview of operations, supports predictive maintenance.
PLC (programmable logic controller)	Industrial computer used to automate/control machinery	Executes programmed logic, responds to sensor inputs, automates repetitive tasks.
HMI (human-machine interface)	Interface letting human operators interact with machines/automation systems	Displays real-time data/alarms/controls to monitor, control, and troubleshoot manufacturing processes.

Digital technology	What it is	Application in (high-tech) manufacturing companies
DCS (distributed control system)	System for controlling complex processes with distributed controllers and centralized monitoring	Automation of continuous processing, increases efficiency and precise control.
Cloud-based storage	Online storage, secure/scalable/remote data access and management	Centralizes production data, supports collaboration across locations.
IIoT (industrial internet of things)	Network of connected industrial devices/sensors that collect and exchange data	Real-time monitoring, predictive maintenance, quality control.
Edge device	Computing device near production line, processes data close to where it's located	Enables real-time data analysis, reduces latency, and improves responsiveness.
Data lake	Central repository that stores large volumes of structured and unstructured data in raw format	Aggregates data from various sources for analytics, machine learning, data-driven decision-making.
Data store	General term for storing and managing data (includes database, data lake, file system)	Stores production, quality, sensor data for retrieval by MES, analytics, or reporting systems.
Data historian	Specialized software for capturing/storing/retrieving time-series data from equipment and processes	Captures real-time and historical process data for monitoring and trend analysis. Integrates with SCADA/MES/ERP.
Database	Structured data storage system, to store/query/manage data	Supports MES/ERP by storing structured data for fast access and analysis.
Industrial connectivity (on-prem)	Software/hardware that connects industrial devices within a local (on-premises) environment	Facilitates data exchange between equipment, PLCs, sensors, enterprise systems.
Digital twin	Virtual, real-time replica of a physical asset, connected to its real-world counterpart	Simulates, monitors, and optimizes production, tests process changes, improves product quality.
APC (advanced process control)	Automated control systems using advanced algorithms/models to optimize complex manufacturing processes	Enhances process stability, quality, and efficiency by continuously updating process parameters. Connects with DCS, SCADA, and data historians.
Manufacturing control tower (MCT)	Centralized platform that provides near-real-time visibility and unified management of manufacturing operations and supply chain activities	Aggregates data from across the enterprise, enables monitoring, performance analysis, and informed decisions on manufacturing and logistics.
SPC (statistical process control)	Quality control method that uses statistics to monitor and control manufacturing processes	Uses real-time data to detect deviations, reduce variability, ensure consistent product quality.
AR (augmented reality)	Technology that overlays digital information onto the real-world environment via smart glasses, tablets, or phones	Assists workers with step-by-step assembly instructions, maintenance guidance, remote support, and training.

Identifying digital technologies supporting ESRS sub-dimensions

With a compiled list of digital manufacturing technologies relevant to the high-tech manufacturing sector, the next step is to match these technologies to the ESRS sub-dimensions selected earlier. This matching allows for the identification of areas where digital technologies can directly support sustainability performance. Specifically, the intersection between relevant ESRS sub-dimensions, representing key sustainability impacts for the Dutch high-tech manufacturing sector, and applicable digital manufacturing technologies defines the potential for the Twin Transition. In other words, the Twin Transition occurs where digital technologies can enhance the performance of sustainability impacts as defined by the ESRS framework.

To establish these connections, each digital manufacturing technology was assessed in relation to the ESRS sub-dimensions, using both academic literature and information provided by technology providers active in the high-tech manufacturing sector. For instance, enterprise resource planning (ERP) systems were found to support the monitoring and planning of production processes, leading to improved equipment efficiency and reduced idle time (SAP SE, 2025). In addition, ERP-driven schedule optimization can align machine usage with lower energy-cost periods, thereby reducing overall energy consumption (ECI, 2024). Based on this evidence, ERP systems are considered to contribute positively to ESRS E1-5 (energy use and mix).

A detailed explanation of how each digital technology contributes to one or more ESRS impacts is provided in Section D.2.6 of Appendix D.2. After completing the literature and data review, the resulting overview was presented to two interview participants. These interviews, part of the first design cycle, helped validate and refine the technology-to-impact connections. Further details on the interview process and summaries can be found in Appendix D.2.7. Based on feedback from these interviews, the overview was updated accordingly. The final mapping of digital technologies to relevant ESRS impacts is presented in Table 5.6.

Firstly, during the interviews it was confirmed that whenever a digital manufacturing technology contributes positively to ESRS E1-5 (energy consumption and energy mix), it will also affect ESRS 1-6 (GHG emissions) positively. This is because the GHG emissions in Scope 2 (origin from energy used) are reduced if the amount of energy is used or if renewable/low-carbon energy is used. Furthermore, neither the literature nor the interviewees could identify a link between a digital manufacturing technology and ESRS S1-8 (representation). Therefore, in Table 5.6 this impact is excluded, meaning that it is not an ESRS impact that (with these digital manufacturing technologies and with the knowledge at this moment) is part of the Twin Transition for the high-tech manufacturing sector and is therefore not part of the decision-support tool based on these insights. Moreover, it stood out that the interviewees also identified multiple social and governance impacts that were previously not identified with the literature. They saw for example how remote work, enabled by the digital manufacturing technologies, could lead to improved diversity (S1-9) and work-life balance (S1-15) for employees. Also digital manufacturing technologies that support transparency in manufacturing could support ethical behavior (G1-1). No new technologies were identified by the interviewees that could be classified as digital manufacturing technologies.

Table 5.6: Overview of which of the selected digital manufacturing technologies relevant to the Dutch high-tech manufacturing sector can support sustainability performance across which ESRS impact categories. These digital manufacturing technologies and these ESRS impact categories are therefore the Twin Transition dimensions included in the maturity assessment and decision-support tool.

Digital manufacturing technology	E1-5 (Energy consumption and mix)	E1-6 (GHG emissions)	E2-4 (Air pollution)	E2-5 (Use of hazardous chemicals)	E5-4 (Resource consumption)	E5-5 (Waste & circularity)	S1-9 (Diversity & inclusion)	S1-13 (Training & skills)	S1-14 (Occupational health & safety)	S1-15 (Work-life balance)	G1-1 (Ethical culture and behavior)
ERP	X	X		X		X					
APS	X	X				X					
MES	X	X		X	X	X				X	X
SCADA	X	X									
PLC	X	X				X					
HMI	X	X						X		X	X
DCS	X	X	X								
Cloud-based storage	X	X						X			
IIoT	X	X		X		X					
Edge device	X	X		X		X					
Data lake/store/base	X	X									
Data historian	X	X		X		X					
Industrial connectivity (on prem)	X	X									
Digital twin	X	X				X				X	
APC	X	X	X			X					

Digital manufacturing technology	E1-5 (Energy consumption and mix)	E1-6 (GHG emissions)	E2-4 (Air pollution)	E2-5 (Use of hazardous chemicals)	E5-4 (Resource consumption)	E5-5 (Waste & circularity)	S1-9 (Diversity & inclusion)	S1-13 (Training & skills)	S1-14 (Occupational health & safety)	S1-15 (Work-life balance)	G1-1 (Ethical culture and behavior)
MCT	X	X			X	X			X		X
SPC	X	X	X	X		X			X		
AR	X	X			X	X	X	X	X	X	

Overview of the selected dimensions and sub-dimensions

Integrating the two sets of selected dimensions, People, Process & Policy (PPP) and Environmental, Social & Governance (ESG), with the relevant sub-dimensions from the ESRS impact categories identified for the Dutch high-tech manufacturing sector results in the following hierarchy: the model's main dimensions are People, Process, and Policy. Each of these is divided into the three sustainability dimensions: Environmental, Social, and Governance. These ESG dimensions are then further broken down into the specific ESRS impact categories relevant to the sector. This full dimension hierarchy is visualized in Figure 5.2.

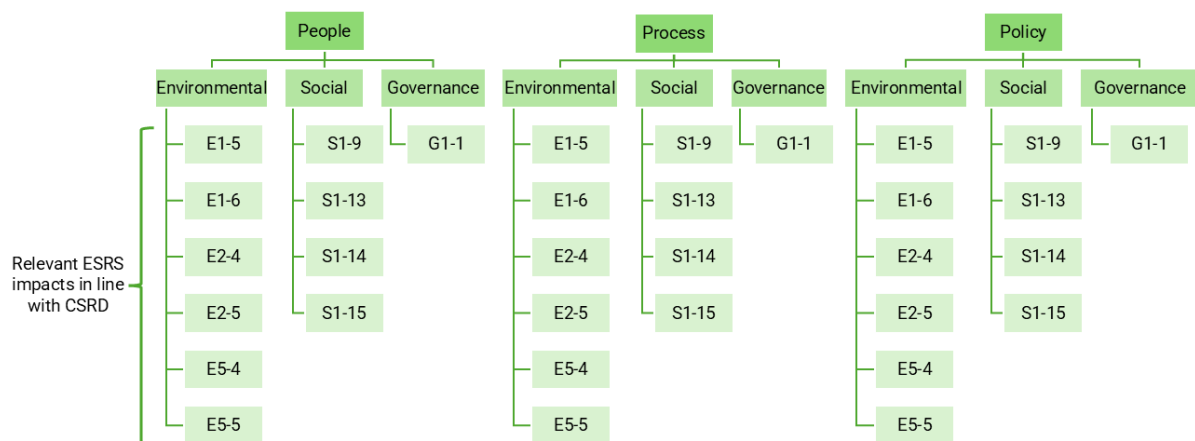


Figure 5.2: Overview of how the People, Process & Policy dimensions connect to the ESG sustainability dimensions and sub-dimensions.

5.2.5. Review and selection of levels

With the relevant dimensions and sub-dimensions now selected for the Twin Transition maturity assessment, the next step is to define maturity levels that reflect how digital technologies contribute to sustainability in the Dutch high-tech manufacturing sector.

Review of the foundation model levels

The Accenture Industry Sustainability Maturity Model defines four maturity levels: “not implemented” (score 0–1.1), “partially implemented” (1.2–2.4), “largely implemented” (2.5–3.7), and “fully implemented” (3.8–5.0). These levels are used to assess the implementation status of sustainability-related practices such as strategic sourcing, reverse logistics, or life-cycle analysis.

At first glance, this model could also be applied to digital technologies. For example, an enterprise resource planning (ERP) system could similarly be categorized as not implemented, partially imple-

mented, or fully implemented. However, a closer examination shows that this approach is not appropriate for the purpose of the Twin Transition maturity assessment. The reason is that implementation alone does not determine whether a digital technology actually contributes to sustainability outcomes. Many digital technologies in manufacturing are adopted primarily to improve operational performance, reduce costs, or increase production flexibility. While these technologies have the potential to support sustainability impacts, their contribution depends heavily on how they are applied. For example, an ERP system might be fully implemented but used solely for financial and logistics purposes, without any connection to energy monitoring or sustainability reporting. In such a case, the technology would have little to no impact on ESG performance, despite being technically “fully implemented.” This makes maturity levels based on implementation status inadequate.

Rationale for digital maturity levels

For the Twin Transition context, maturity must instead be defined in terms of how digital capabilities are leveraged to amplify sustainability performance. In other words, what matters is not just whether a technology is in place, but whether it is actively contributing to relevant ESG outcomes. Therefore, maturity levels in the Twin Transition assessment are built from the perspective of digital maturity.

This approach also reflects the underlying essence of the Twin Transition: sustainability performance can be improved more effectively when enabled or accelerated by digital technologies (Hellemans and Oostervink, 2025). It shifts the focus from technological coverage (i.e. how broadly a system is implemented) to technological impact (i.e. how meaningfully a system supports ESG goals).

Moreover, grounding the model in digital maturity makes it possible to integrate an important limitation of the Twin Transition. While digital technologies can enhance sustainability outcomes, they are not a complete solution. For example, a digital twin might help optimize energy use or reduce scrap rates, thereby contributing to lower emissions. However, it cannot eliminate emissions entirely, nor can it replace physical changes such as switching to renewable energy sources or redesigning supply chains (Tzachor et al., 2022). In fact, some digital technologies themselves consume energy, generating their own Scope 2 emissions (Muñoz de Bustillo Llorente, 2024). This means that the Twin Transition can only take sustainability so far, up to the point where digital technologies can still create an impact. Beyond that, other types of interventions are needed (Muñoz de Bustillo Llorente, 2024). A maturity model built solely around sustainability implementation would not reflect this boundary. But a model rooted in digital maturity inherently recognizes this limit: it shows how far digital can take a company toward its sustainability targets, without suggesting that digital alone is sufficient.

Selection of suitable digital maturity levels

To determine how many and what types of maturity levels are appropriate for the Twin Transition maturity model in high-tech manufacturing, a focused literature review was conducted. This review examined existing systematic literature reviews on digital maturity models in the manufacturing sector. The search included terms such as digital maturity, smart manufacturing maturity, Industry 4.0 maturity, and digital manufacturing maturity, and was conducted in both Scopus and Web of Science. Although no review papers specifically addressed high-tech manufacturing (as of 12 May 2025), general manufacturing-focused reviews were considered the most relevant alternative. Compared to models from other manufacturing sectors, these better reflect the operational context of high-tech manufacturing. To further align with the scope of this research, papers were also filtered to include only those focusing on large manufacturing firms, as maturity trajectories can differ significantly for SMEs, and might therefore provide non-relevant conclusions for the LEs that are the scope of this research. Four systematic review papers met all criteria and were included in the analysis, Appendix D.3, Table D.8 provides an overview of these selected papers and their focus.

Across the selected reviews, there is a strong consensus on the general structure of digital or Industry 4.0 maturity models. Table 5.7 summarizes the levels defined in each review. While terminology varies, the reviews converge on a shared maturity trajectory. Maturity typically begins with isolated digital tools, progresses through stages of connectivity and integration, and ends in predictive and autonomous systems.

Table 5.7: Digital maturity levels as identified by multiple systematic reviews.

Angreani et al. (2020)	Souhail et al. (2023)	Ünlü et al. (2024)	Vance et al. (2023)
1. Initial: little to no digitization, manual	1. Novice: no/low digital integration	1. Initial: no strategy for digital	1. Computerization: standalone digital solutions
2. Basic: use of digital systems, in silos	2. Aware: exist, but not integrated	2. Initiation: isolated applications of digital tools	2. Connectivity: devices and systems communicate
3. Integration: integrated systems, enabling information exchange	3. Competent: integration and use	3. Integration: IT/OT convergence	3. Visibility: monitoring enabled by data flow
4. Measured: data is captured and analyzed	4. Advanced: end-to-end integration, real-time dashboards	4. Data-driven: analysis guides operational decisions	4. Transparency: data contextualized and interpreted
5. Predictive: real-time data is used to optimize and anticipate production behavior	5. Leader: predictive and autonomous systems	5. Predictive & optimizing: enable forecasting and optimized control	5. Predictive capability: forecasting and scenario simulation
			6. Self-adjusting systems based on automation

While the maturity levels identified in the four selected review papers provide a strong starting point, not all are directly applicable to the scope of the Twin Transition maturity model. This model focuses exclusively on manufacturing operations within Dutch high-tech manufacturing firms. In contrast, many of the reviewed models extend beyond the production floor, addressing enterprise-wide digital strategies and cross-departmental integration. These broader scopes are not suitable for the Twin Transition, which aims to assess how digitalization specifically supports operational and sustainability improvements at the level of production processes.

To ensure alignment with this narrower and more focused scope, the maturity levels identified in the literature were systematically reviewed and reinterpreted through the lens of data analytics maturity. This perspective is particularly appropriate for two key reasons. First, the way data is collected, interpreted, and used is central to digital transformation. Digital maturity closely follows the sophistication of data use, making data analytics a fitting lens to trace operational progress from basic digital tools to autonomous systems (Król and Zdonek, 2020). Second, data analytics maturity focuses on how effectively data supports decision-making, rather than just the presence of digital systems (Król and Zdonek, 2020). This aligns with the Twin Transition's emphasis on operational impact, allowing for a more targeted assessment of how digitalization improves efficiency and sustainability within manufacturing processes.

The first level across all four systematic reviews consistently refers to the early stages of digitalization. At this stage, digital tools are present but used in isolation, with very limited integration or automation. Examples include local sensors or machines equipped with basic human-machine interfaces, without any centralized monitoring or data analytics capability. From the perspective of data analytics literature, this level is associated with descriptive analytics (Roy et al., 2022). Data is used to generate alerts, dashboards, or visualizations that support operators in answering the question: what is happening? There is no deeper analysis or contextualization of the data at this point. This level is directly applicable to the Twin Transition model and requires no adaptation, as it accurately reflects the foundational use of digital tools within manufacturing operations.

The second and third levels in the maturity literature typically describe increasing levels of connectivity and system integration. These stages often involve interdepartmental data flows or IT/OT convergence at the enterprise level. However, such cross-functional integration lies outside the intended scope of the Twin Transition model, which is limited to manufacturing operations themselves, not enterprise-wide digital infrastructure. As a result, these levels were excluded. Although they are relevant in broader digital transformation efforts, they do not align with the specific operational focus of this maturity model.

The fourth level in the review papers is where data becomes integrated and accessible in real time across the production process. At this stage, digital systems collect and structure data in ways that allow it to be contextualized and analyzed to support decision-making. According to data analytics literature, this aligns with the concept of diagnostic analytics, where digital tools help operators understand

why something happened (Roy et al., 2022). For example, deviations in machine performance can be traced back to specific process variables or historical trends. While this level is already present in the maturity literature, it is adapted here to emphasize the analytical aspect of data use, moving beyond visibility and integration toward purposeful diagnosis.

The fifth level across the literature reviews focuses on predictive capabilities. At this stage, digital systems not only describe or diagnose but also anticipate potential issues or future conditions. Predictive maintenance, yield forecasting, and anomaly detection are examples of tools used at this level. This clearly maps onto the predictive analytics stage in data analytics literature, where historical and real-time data are used to answer the question: what will happen? (Roy et al., 2022). The Twin Transition model should incorporate this level directly, as it remains within the scope of manufacturing operations. The key adaptation made here is to explicitly define this level in terms of how predictive analytics informs human action, rather than assuming full autonomy immediately.

Some of the systematic reviews introduce a final, sixth level, where systems become autonomous and self-regulating. These are often described as self-adjusting systems that no longer require human intervention for most operational decisions. However, data analytics literature introduces a more nuanced progression by identifying a distinct stage between predictive and autonomous systems: prescriptive analytics (Roy et al., 2022). At the prescriptive level, systems not only forecast outcomes but also recommend specific, optimized actions to be taken. These recommendations are delivered to operators. This stage supports decision-making with advanced reasoning and optimization, allowing operators to answer the question: what should we do? (Roy et al., 2022). This prescriptive level is not explicitly identified in the maturity models from the literature review, but it is important from an analytics standpoint. Therefore, it is added as a separate, fifth level in the Twin Transition maturity model.

The final level, as described in both the systematic reviews and data analytics literature, involves adaptive or autonomous systems (Roy et al., 2022). These are systems that learn over time, self-optimize, and act without direct human input. In manufacturing, this might include dark factories, where production is fully automated and decisions are made by AI-driven systems. In data analytics, this corresponds to adaptive analytics, where the system continuously evolves based on feedback loops and ongoing data input (Roy et al., 2022). This level is included in the Twin Transition maturity model as the final stage of digital maturity, representing the highest degree of operational intelligence achievable through digital transformation.

Figure 5.3 summarizes the resulting five-level maturity structure developed for the Twin Transition model. These levels are grounded in both data analytics and manufacturing maturity literature and tailored to reflect the digital evolution of manufacturing operations specifically.

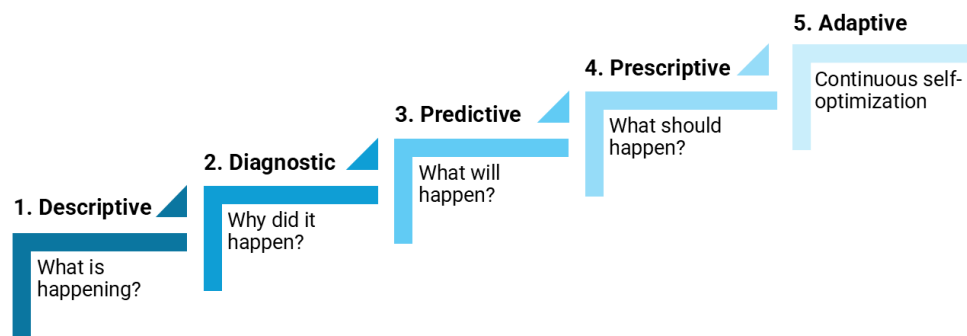


Figure 5.3: Overview of the 5 digital maturity levels used for the Twin Transition maturity model.

5.2.6. Populating the Twin Transition maturity model for Dutch high-tech manufacturing

By combining the dimensions, sub-dimensions and the levels defined in the sections above (and as shown in Figure 5.2, the Twin Transition maturity model for the Dutch high-tech manufacturing sector can be populated.

For each of the sub-dimensions, the 5 digital maturity levels need to be assessed. The connection

between the digital maturity levels and the sustainability impacts is based on the digital manufacturing technologies in Table 5.6. Filling the Twin Transition maturity model for the Dutch high-tech manufacturing sector is then done in two steps:

1. Digital maturity for technologies: for every digital manufacturing technology listed in Table 5.6, it is determined how each digital maturity level (from descriptive to adaptive) looks for that technology. Basically this step answers: what can each digital manufacturing technology do at each digital maturity level?
2. Digital maturity overlap with sustainability: for every digital maturity technology at every digital maturity level, it is determined how their sustainability impact would look like based on their sustainability applications as outlined in Appendix D.2, Section D.2.6.

Digital maturity of digital manufacturing technologies

For each digital maturity technology listed in Table 5.6, its capabilities were assessed across the five digital maturity levels: descriptive, diagnostic, predictive, prescriptive, and adaptive. This assessment was based on internal Accenture materials and on X. A detailed overview of how each technology functions at each maturity level is provided in Appendix D.4, Table D.9.

For example, at the descriptive level, a digital twin functions primarily as a real-time virtual representation of a physical asset, machine, or process. It mirrors current operating conditions using live sensor data streamed through IIoT devices. This twin provides a dashboard view, offering visibility into parameters such as temperature, speed, pressure, or cycle time, just like a high-resolution mirror reflecting factory operations.

As the system matures to the diagnostic level, the digital twin becomes capable of replaying historical data and simulating failure scenarios to aid in root-cause analysis. Engineers can use the model to visualize how deviations or errors unfolded over time.

At the predictive stage, the digital twin uses historical data patterns and simulation models to forecast future outcomes under different conditions. This involves running "what-if" analyses to evaluate the impact of variable changes (e.g., raw material properties, environmental shifts, or new product configurations).

When a digital twin reaches the prescriptive level, it not only simulates but also recommends optimized actions based on its models. The twin is integrated with control systems (e.g., APC, MES, PLC), allowing it to push recommended parameter changes directly to machines.

At the highest, adaptive maturity level, the digital twin becomes a self-learning, autonomous agent in a closed-loop cyber-physical system (CPS). It continuously learns from both simulated and real-world outcomes, updating its models autonomously and making real-time decisions without human input.

As shown in this example of the digital twin and also in the assessment in Appendix D.4, Table D.9, digital manufacturing technologies are highly interdependent. In particular, IIoT and edge devices seem to be foundational, enabling the maturity of many other technologies. This highlights that digital technologies do not increase in maturity on their own: advancing the maturity of digital manufacturing technology often depends on the maturity of others already being in place.

Digital maturity in support of sustainability

After establishing the functionality of each digital manufacturing technology across the five digital maturity levels, the next step was to assess their potential sustainability impact at each level. This assessment was done per ESRS sub-category, using the links between technologies and ESRS impacts as identified in Table 5.6.

The process involved comparing the capabilities of each technology at each maturity level (as shown in Table D.9) with their potential sustainability impacts (outlined in Appendix D.2, Section D.2.6). Based on this comparison, the researcher interpreted how each technology could contribute to sustainability outcomes at different stages of digital maturity. This interpretation was necessary, as no existing sources were available that provided this level of detail. Therefore, the analysis relied on the researcher's judgment to align technological capabilities with relevant ESRS impacts. Table D.10 in Appendix D.4 shows an overview of all the digital manufacturing technologies and their sustainability impact categorized per ESRS sub-dimension at each digital maturity level. Figure 5.4 illustrates how this approach is applied using advanced planning and scheduling (APS) as an example. It shows how

APS can support the ESRS impact category E1-6 (greenhouse gas emissions) across the five digital maturity levels, from descriptive to adaptive.

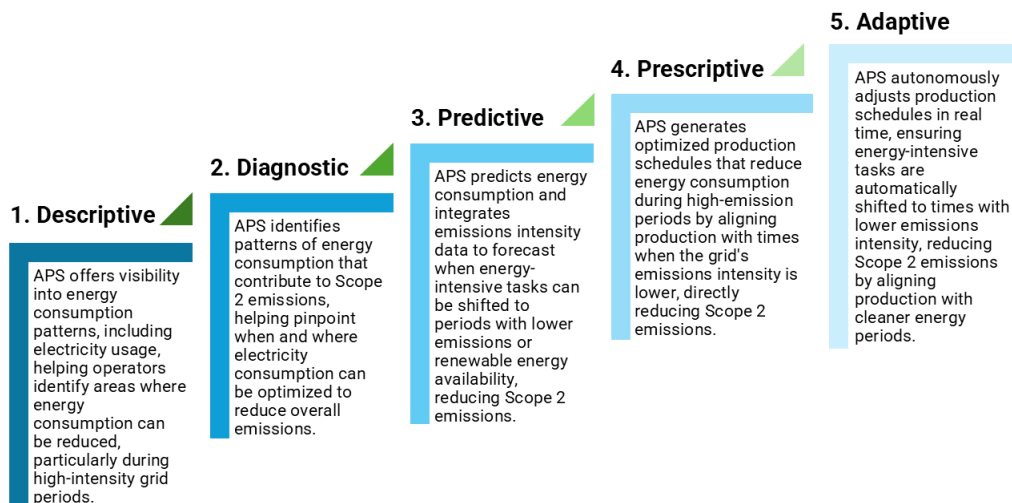


Figure 5.4: Example of how the digital manufacturing technology APS can be used to support the ESRS impact E1-6 (GHG emissions) at each of the five different digital maturity levels.

5.2.7. KPIs: review and adaptation

Following the method proposed by De Bruin et al. (2005), once the maturity levels have been defined and the model populated, the next step is to establish measurable indicators to assess progress within each (sub-)dimension. This section aims to identify indicators that can track how digital maturity in digital manufacturing technologies contributes to the sustainability impacts relevant for the Dutch high-tech manufacturing sector.

As outlined in Section 4.2, these indicators should follow a hierarchical structure aligned with the model's dimensions. At the highest level, there should be an aggregated sustainability score measured with indicators for each of the three main dimensions: People, Process, and Policy. Each of these should then be broken down into aggregated indicator scores for the Environmental, Social, and Governance (ESG) dimensions. Finally, the ESG scores should be further disaggregated into indicators for the specific ESRS impact categories. This Key Performance Indicator (KPI) structure mirrors the dimension hierarchy shown in Figure 5.2.

Review of the foundation model indicators

The Accenture Industry Sustainability Maturity Model uses GRI indicators to assess the sustainability maturity of manufacturing firms. The Global Reporting Initiative (GRI) is an independent international standards organization that provides widely used guidelines for sustainability reporting (DFGE – Institute for Energy, Ecology and Economy, 2017). Its standards are organized into three series: Universal Standards, Sector Standards, and Topic Standards (Global Reporting Initiative, 2021). Sector Standards help organizations identify material topics specific to their sector, but, no Sector Standard currently exists for the high-tech manufacturing sector specifically. The Topic Standards offer detailed disclosures on specific sustainability issues, such as materials, energy, water, emissions, and labor practices (Global Reporting Initiative, 2021).

While the GRI indicators are generally relevant to the sustainability impacts of the Dutch high-tech manufacturing sector and could potentially be adapted to align with the ESG dimensions, they are limited to the sustainability aspect of the Twin Transition. However, they do not account for digital maturity. That is the one of the main components of the Twin Transition maturity model, which aims to assess how increasing digital maturity enhances sustainability performance (Global Reporting Initiative, 2021).

In addition, the GRI framework does not incorporate the People, Process & Policy (PPP) dimensions. For example, environmental indicators primarily address the process dimension, while governance indicators focus only on policy (Global Reporting Initiative, 2021; DFGE – Institute for Energy, Ecology and Economy, 2017). As a result, the GRI indicators leave significant gaps, particularly in capturing progress

across all dimensions and sub-dimensions of the Twin Transition maturity model. Therefore, while useful as a reference, the GRI framework would require substantial adaptation to serve the goals of this model.

Method for selecting suitable indicators

Kibira et al. (2018) outlined a method for defining indicators to measure and monitor sustainable manufacturing at a process level. This is aligned with the scope of this research and therefore a suitable method. Using the method from Kibira et al. (2018) provides a systematic, open, and neutral procedure for selecting relevant KPIs.

The method by Kibira et al. (2018) defines two ways of identifying KPIs: top-down or bottom-up. In top-down, the sustainability goals of a company are used to define KPIs to measure and monitor those sustainability goals. In the bottom-up method, the impacts of the processes inform the selection of KPIs. In the case of this research, it therefore makes more sense to use the bottom-up approach: the sustainability goals and priorities of each high-tech manufacturing firm for which the Twin Transition maturity assessment will be used may differ, but the identification of important sustainability impacts that are specific to this sector in defining the sub-dimensions in Section 5.2.4, will be the same foundation for each company and thus aligns well with the bottom-up approach. The method proposed by Kibira et al. (2018) for selecting suitable KPIs for sustainable manufacturing consists of three main steps, which together provide a structured and systematic approach:

1. **Identification of candidate KPIs:** Begin by identifying KPIs from existing literature, databases, and standardized frameworks. The aim is to leverage already established and validated metrics where possible, to ensure comparability and reduce development time.
2. **Definition of new KPIs:** If there are gaps, i.e., no suitable KPIs exist in the literature for certain impacts, new KPIs should be defined. The defined KPIs should follow a consistent format to ensure clarity and facilitate stakeholder understanding and communication.
3. **Selection, ranking, and composition of KPIs:** If needed, the selected KPIs are normalized, weighted according to their importance, and organized into a coherent structure that aligns with the overall sustainability strategy of the manufacturing company.

Selecting suitable indicators

The goal of the indicators for the Twin Transition maturity assessment is to track how the increased digital maturity leads to increased sustainability performance. This should be done for each of the sustainability dimensions (ESG) within each of the implementation dimensions (PPP). As not every Dutch high-tech manufacturer will implement or can implement each of the digital manufacturing technologies, it makes sense that the KPIs are not related to specific digital manufacturing technologies, but that the selected indicators track the digital maturity and sustainability impact across different digital manufacturing technologies. Next to that, as it was mentioned both in the interviews in Section 4.2 and Section D.2.7 by interviewees that fit the intended target user profiles, they want a KPI hierarchy. Therefore, KPIs will first be created for the bottom of the KPI hierarchy: the most detail that is specific to each of the ESRS impact categories. Subsequently, these will be aggregated into KPIs for the E, S and G impacts per and lastly these will be aggregated into a compound sustainability indicator for each People, Process and Policy dimension.

To determine appropriate KPIs for each ESRS impact within the dimensions of PPP, the relevant digital manufacturing technologies were across different levels of digital maturity. These maturity levels, ranging from descriptive to adaptive, are detailed in Table D.9 in Appendix D.4. For each ESRS impact, all technologies were reviewed at a specific maturity level and a general description for each digital maturity level across the three PPP dimensions was developed for all technologies. These descriptions illustrate how the application of digital manufacturing technologies evolves to support ESRS impacts as organizations progress through the five maturity stages. An overview of these descriptions is presented in Table D.11.

Following this, a specific KPI for each ESRS impact within each PPP dimension was defined to track the common maturity level descriptions per ESRS impact presented in Table D.11, tailored to the characteristics of that dimension. To ensure consistency, the descriptions for each KPI across impacts within a dimension follow a standardized structure, while still being specific to the ESRS impact in question.

- **People dimension:** The selected KPI is *competency*, which reflects the level of skill and knowledge employees have in applying digital technologies to support the relevant ESRS impact. This KPI is informed by the work of (Sarria and Pastor, 2018), who propose an indicator for assessing employee skill levels in relation to manufacturing operations.
- **Process dimension:** The chosen KPI is *intelligence*, capturing the extent to which processes are autonomous and capable of self-regulation. In essence, it measures how independently systems can operate. This KPI builds on the framework proposed by (Swarnakar et al., 2022), which includes indicators for the adoption of autonomous systems in manufacturing environments.
- **Policy dimension:** The KPI used is *integration*, which assesses how well digital manufacturing technologies are embedded in the company's sustainability strategies and policies. This draws on the indicators developed by (Gani et al., 2023), which emphasize the policy-driven integration of sustainability into business practices.

Table 5.8: Overview of selected ESRS impact indicators for digital manufacturing technologies.

ESRS impact	People	Process	Policy
E1-5	Digital energy consumption competency	Digital energy consumption intelligence	Digital energy consumption policy integration
E1-6	Digital Scope 1 emissions competency	Digital Scope 1 emissions intelligence	Digital Scope 1 emissions policy integration
E2-4	Digital air pollutant emissions competency	Digital process air pollutant emissions intelligence	Digital air pollutant emissions policy integration
E2-5	Digital hazardous chemical use competency	Digital hazardous chemical use intelligence	Digital hazardous chemical use policy integration
E5-4	Digital material and resource efficiency competency	Digital total resource consumption intelligence	Digital resource use policy integration
E5-5	Digital waste management competency	Digital waste management intelligence	Digital waste management policy integration
S1-9	Digital diversity & inclusion competency	Digital inclusion intelligence via accessible digital tools	Digital tools supporting diversity and inclusion policy integration
S1-13	Digital training & skills competency	Digital skills development intelligence	Digital tools supporting training & skills policy integration
S1-14	Digital occupational health & safety competency	Digital occupational health & safety intelligence	Digital occupational health & safety policy integration
S1-15	Digital work-life balance competency	Digital work-life balance intelligence	Digital work-life balance policy integration
G1-1	Digital ethical behavior & culture competency	Digital ethical behavior and culture intelligence	Digital ethical behavior and culture policy integration

KPIs for ESG in People, Process, Policy

The second level of aggregation involves calculating an overall score for each ESG category, within each of the PPP dimensions. These scores are computed as the weighted average of the ESRS impacts associated with each respective ESG category. For example, the Social (S) score is calculated as the weighted average of the ESRS impact scores for diversity & inclusion, training & skills, occupational health & safety, and work-life balance. The weights used in this calculation are determined by the Dutch high-tech manufacturing company being assessed, allowing the organization to assign relative importance to each ESRS impact based on its strategic priorities and context.

KPIs for sustainability scores in People, Process, Policy

The third level of aggregation produces a single sustainability score for each of the People, Process, and Policy dimensions. These scores are calculated as weighted averages of the ESG composite scores established in the previous step. The weighting scheme for this aggregation is also not fixed, instead, it is defined in collaboration with the assessed high-tech manufacturing company. This approach ensures that the final scores align with the company's strategic focus. For instance, a company facing increased regulatory scrutiny may place more emphasis on governance-related metrics, while a company undergoing workforce transformation may choose to prioritize social indicators.

5.3. Developing a next-step overview to support decision-making

With the Twin Transition maturity model now defined, it becomes possible to assess the current state of a Dutch high-tech manufacturing company in terms of how digital maturity supports sustainability performance. This assessment forms the basis for guiding companies toward targeted improvements.

The next step is to design a decision-support overview that helps companies understand how to move toward their sustainability goals. In line with the model requirements outlined in Section 4.2, this framework should support companies in making informed investment decisions in digital manufacturing technologies. Specifically, it should help identify which technologies contribute to their sustainability goals, where potential trade-offs exist between Environmental, Social, and Governance (ESG) dimensions, and what the implications are for implementation.

While initial requirements included the need for a return-on-investment assessment for each technology, expert interviews conducted during Design Cycle 1 (see Section D.2.7) revealed that ROI data is often not available or reliable at the level of detail needed. Instead, implementation complexity was identified as a meaningful and practical substitute. Understanding how difficult or resource-intensive a technology is to implement can still support prioritization and planning.

Therefore, the design of the next-step overview consists of two core elements:

1. An identification of potential negative sustainability impacts for each digital manufacturing technology, in order to highlight trade-offs between ESG dimensions.
2. An assessment of the complexity of implementing each technology to achieve sustainability impact.

5.3.1. Identification of negative sustainability impacts of each digital manufacturing technology

To identify the trade-off between the sustainability impacts of each digital manufacturing technology (that is, to understand both what each technology contributes to sustainability and what it costs in terms of sustainability) the negative impacts of each technology on the relevant ESRS impact categories were assessed. This analysis was carried out for all technologies listed in Table D.7. The evaluation was based on a combination of academic literature and information provided by the companies that develop and supply these digital manufacturing technologies to high-tech manufacturing firms. Each technology was reviewed in relation to its effects on the ESRS impact categories introduced earlier, with a focus on identifying potential negative outcomes.

For instance, augmented reality (AR) in high-tech manufacturing often relies on head-mounted displays or tablets, supported by backend systems that deliver AR content such as 3D models and live video feeds. Operating AR systems can be energy-intensive, as rendering graphics, running sensors (e.g., cameras, GPS, IoT integrations), and transmitting data all require substantial electricity. When AR is deployed at scale (for example, using hundreds of AR goggles for training or assembly assistance) the energy required to charge these devices and maintain the supporting wireless infrastructure increases significantly. The need for computing power is also considerable, particularly when using cloud-based AR platforms or real-time remote expert support. Consequently, AR is identified as having a negative impact on ESRS 1–5, which relate to energy consumption.

A more detailed explanation of how each digital manufacturing technology influences the ESRS impact categories can be found in Section D.6.1 of Appendix D.6. Table 5.9 provides an overview of which technologies, relevant to the Dutch high-tech manufacturing sector, are associated with negative sustainability impacts across specific ESRS categories.

Table 5.9: Overview of which of the selected digital manufacturing technologies relevant to the Dutch high-tech manufacturing sector can negatively affect sustainability performance across specific ESRS impact categories.

Digital manufacturing technology	E1-5 (Energy consumption and mix)	E1-6 (GHG emissions)	E2-4 (Air pollution)	E5-5 (Waste & circularity)	S1-9 (Diversity & inclusion)	S1-14 (Occupational health & safety)	S1-15 (Work-life balance)	G1-1 (Ethical culture and behavior)
ERP (enterprise resource planning)	X	X		X	X	X	X	X
APS (advanced planning and scheduling)	X	X		X	X	X	X	X
MES (manufacturing execution system)	X	X	X	X	X	X	X	X
SCADA (supervisory control and data acquisition)	X	X				X	X	X
PLC (programmable logic controller)	X	X		X	X	X	X	
HMI (human-machine interface)	X	X			X	X		X
DCS (distributed control system)	X	X	X	X		X	X	X
Cloud-based storage	X	X	X	X				
IIoT (industrial internet of things)	X	X		X			X	
Edge device	X	X		X		X		X
Data lake/store/base	X	X	X	X				
Data historian	X	X	X	X				
Industrial connectivity (on prem)	X	X		X		X		
Digital twin	X	X		X		X		
Advanced process control	X	X		X		X	X	X
Manufacturing control tower	X	X		X		X	X	X
Statistical process control	X	X		X		X		
Augmented reality	X	X		X	X		X	X

Digital maturity and negative impacts on sustainability

After identifying the potential negative sustainability impact of each digital manufacturing technology across the five digital maturity levels, the next step was to evaluate their potential negative sustainability impacts at each level.

This evaluation was conducted for each ESRS sub-category, based on the established links between technologies and ESRS impacts presented in Table D.7. The assessment process involved a comparison between the capabilities of each technology at each maturity level (as detailed in Table D.9) and their corresponding potential sustainability impacts (described in Section D.6.1 of Appendix D.6). Through this comparison, the researcher interpreted how the implementation of each technology might influence sustainability outcomes at various stages of digital maturity.

Since no existing sources offered this level of detailed analysis, the interpretation relied on the researcher's judgment to align technological capabilities with the relevant ESRS impacts. A summary of the results, showing all digital manufacturing technologies and their negative sustainability impacts, categorized by ESRS sub-dimension and digital maturity level, is provided in Table D.12 in Appendix D.6.

Trade-off determination

Table 5.9 shows that many digital manufacturing technologies that negatively affect a specific ESRS impact category can also support that same category, as indicated in Table D.7. This raises an important question: does a digital manufacturing technology have a net positive or net negative effect on a particular ESRS impact? The answer to this determines whether the technology should be recommended to improve that specific sustainability area. An overview of the trade-offs, where a single technology both positively and negatively affects the same ESRS impact, is provided in Table D.13 in Appendix D.6.

As discussed in Section 5.2.6 and Section 5.2.6, how a digital manufacturing technology is used plays a major role in the extent of its positive impact. To understand the net effect of each technology, both positive and negative impacts were compared across digital maturity levels for each ESRS category. This trade-off analysis can be found in Section D.6.4 of Appendix D.6.

Several patterns emerge from this comparison. For energy consumption and greenhouse gas emissions, a clear trend is visible. In nearly all cases (13 out of 18 technologies), the descriptive level shows a net negative impact, meaning energy use and emissions increase when these technologies are first implemented. However, as the digital maturity level rises, the net benefits also increase. This highlights an important point: it's not just the technology itself that leads to better sustainability outcomes, but how it is used. As data becomes more intelligently applied, through higher levels of digital maturity, the potential for energy and emission savings grows.

In the case of air pollution and circularity, the environmental costs of implementing digital manufacturing technologies are relatively minor compared to the gains. As a result, these technologies consistently deliver a net positive effect in these areas.

The same is true for diversity and inclusion, as well as occupational health and safety. While there may be some initial challenges for employees adapting to new technologies, these tend to diminish over time, especially when the technologies are applied with social goals in mind. Ultimately, they contribute positively to these social ESRS impacts.

On the other hand, when it comes to work-life balance and the impact on ethical behavior and organizational culture, digital manufacturing technologies tend to have a net negative effect, especially at higher maturity levels. This is because these technologies often increase employee surveillance and can lead to more intense or longer work hours, as remote and digital tools make constant availability more likely. These impacts are also interconnected: heightened monitoring (a governance concern) can contribute to diminished work-life balance (a social concern), making the overall effect worse.

5.3.2. Identification of implementation complexity of each digital manufacturing technology

Insights from the interviews conducted during the first design cycle of the decision-support tool revealed that assessing ROI or the broader economic dimension of implementing digital manufacturing technologies for sustainability purposes would not yield meaningful results. This is mainly due to the frequent lack of reliable data. As a result, implementation complexity was chosen as a more practical and informative substitute.

In this study, implementation complexity is not evaluated based on how difficult a digital manufacturing technology is to implement in general. Instead, it focuses specifically on how complex it is to implement for a given sustainability impact at a particular digital maturity level. This focus was determined through internal discussions at the internship company.

This distinction is important because every factory operates with a unique system setup, configuration, and level of integration. These differences make general assessments of implementation complexity too broad to be useful. Moreover, many factors that affect overall implementation, such as legacy systems or vendor lock-in, may have little relevance when evaluating sustainability outcomes.

Therefore, complexity is assessed based on how easily a technology can be adapted to support a specific sustainability goal. During the interviews in design cycle 1, it was suggested to classify this complexity into three relative levels: low, medium, and high (see Section D.2.7 for the full interview summaries). In the context of this study, these levels are defined as follows:

1. **High complexity:** The technology is applied in a way that differs significantly from its original design. Its implementation may disrupt productivity, conflict with existing business processes, or require substantial customization. This is particularly challenging in high-tech, continuous production environments such as 24/7 operations.
2. **Medium complexity:** This falls between high and low. The implementation may involve some adjustments or custom integration, but it is not fundamentally misaligned with existing systems or workflows.
3. **Low complexity:** The technology fits well within the current system and business objectives. It can be implemented with minimal modifications and does not require overriding core functions.

Since complexity in this study is defined specifically by how technologies are applied for sustainability purposes, and since this application varies across digital maturity levels, the complexity was assessed for each digital manufacturing technology, at each maturity level, and for each ESRS impact. An overview of the implementation complexity associated with using digital manufacturing technologies for sustainability is presented in Table D.14 in Appendix D.6.5.

Table D.14 shows that at the lowest maturity level, the sustainability use case typically aligns with the original purpose of the technology. As a result, it rarely interferes with existing business operations, and implementation complexity is generally low. However, beginning at the second level of maturity (diagnostic), implementation complexity is almost always rated as medium. This shift reflects the need for deeper integration and more tailored usage of the technology.

At the prescriptive level (maturity level 4), implementation complexity is often rated as high. At this stage, technologies must be used in ways that differ significantly from their standard applications, often requiring advanced data use and integration with systems such as artificial intelligence.

For example, using ERP systems at the adaptive level to optimize energy consumption (E1-5) is rated as high complexity. This is because it demands real-time optimization and AI integration, capabilities that are not typically part of standard ERP setups in the high-tech manufacturing sector.

Another example is the use of augmented reality (AR) to promote diversity and inclusion (S1-9) at the prescriptive level. This is also rated as high complexity, as it requires real-time adaptation of instructions to meet diverse accessibility needs (e.g., through voice commands or visual adjustments). Achieving this level of personalization and configurability demands significant customization, which is rarely implemented in current AR applications within manufacturing environments.

5.4. Integration: decision-support tool development

Integrating all the elements from the decision-support tool development, the three sub-parts (the survey, the maturity assessment and the next-steps overview) will be integrated in the way that is described below to support Dutch high-tech manufacturing companies in improving their Twin Transition through using digital manufacturing technologies to improve their sustainability performance.

5.4.1. Survey: determining the priorities and maturity level

The survey begins by providing brief explanations to support users, as the intended user group (defined in Section 4.1.3) may not consist of sustainability specialists. It offers a short introduction to the Twin Transition, outlines the relevant regulatory context (including CSRD and ESRS), and explains which ESRS impacts are included in the assessment. Additionally, the ESG and PPP frameworks are briefly introduced to provide a foundation for understanding the survey structure.

After this introduction, participants are guided through a series of steps to define their sustainability priorities and maturity levels.

Weighting determination

Participants first assign a score from 1 to 3 to each of the Environmental, Social, and Governance (ESG) dimensions, indicating how important they consider each one.

They can then choose which ESRS impact categories to include in the assessment. For example, a participant might choose to include energy consumption (ESRS E1-5) but exclude greenhouse gas emissions (ESRS E1-6). For each ESRS impact selected, participants answer follow-up questions. They first rate the importance of that impact on a scale from 1 to 4 (1 = slightly important, 2 = moderately important, 3 = very important, 4 = essential). Next, they are asked to indicate their current and target maturity levels for each of the three PPP dimensions: people, process, and policy.

This approach to weighting the ESG and ESRS priorities reflects the tool's intention to incorporate company-specific focus areas, allowing for more tailored results. However, it is important to note that this method could obscure a company's weaker areas and result in a biased maturity score. Therefore, the tool should clearly communicate to users that their selected priorities might influence the outcome, and that it could be valuable to also explore sustainability areas outside their current focus.

Maturity score determination

As in the Accenture Industry Sustainability Maturity Model, the maturity levels are presented directly to the participant. These levels, described in Table D.11, range from 1 to 5. Participants are asked to identify both their current and target maturity level for each selected ESRS impact. These inputs are then used to calculate overall maturity scores.

5.4.2. Maturity assessment: maturity score calculation

From the survey responses, the qualitative maturity levels selected by the user are translated into numerical scores. The five maturity levels correspond to the following numerical values: *descriptive* = 1, *diagnostic* = 2, *predictive* = 3, *prescriptive* = 4, and *adaptive* = 5. Based on these values, a maturity score is calculated for each selected ESRS impact, across each of the three PPP dimensions (People, Process, and Policy).

The first level of aggregation computes the Twin Transition maturity scores per PPP dimension, separately for the Environmental (E), Social (S), and Governance (G) categories. During the survey, the participant rates the importance of each ESRS impact on a scale from 1 to 4. This rating is used as a weight and is referred to as the *ESRS weight*. The maturity score for each ESG category within a PPP dimension is calculated using the following formula:

$$PPP_{ESG} = \frac{\sum_{i=1}^n (ESRS \text{ score}_i \times ESRS \text{ weight}_i)}{\sum_{i=1}^n ESRS \text{ weight}_i} \quad (5.1)$$

Where PPP_{ESG} is the normalized score (1-5) for a specific ESG dimension within a PPP dimension. n is the number of ESRS impacts in the ESG dimension, which depends on how many ESRS impacts the survey taker wanted to include. $ESRS \text{ score}_i$ is the maturity score for ESRS impact i and $ESRS \text{ weight}_i$ is the importance weight for ESRS impact i assigned by the survey taker.

This calculation is performed for Environmental (E), Social (S), and Governance (G) dimensions within each People, Process, and Policy dimension.

The second level of aggregation computes the overall Twin Transition maturity scores for each PPP dimension, combining all three ESG categories. At the beginning of the survey, the participant has also rated the importance of each ESG dimension on a scale from 1 to 3; this rating is used as the *ESG weight*. The calculation for each PPP dimension is:

$$PPP_{Total} = \frac{\sum_{j \in E, S, G} (Score_{PPP_j} \times ESG \text{ weight}_j)}{\sum_{j \in E, S, G} ESG \text{ weight}_j} \quad (5.2)$$

Where PPP_{Total} is the overall normalized score (1-5) for a PPP dimension. PPP_j is the score for an ESG dimension j within the PPP dimension. The $ESG \text{ weight}_j$ is the importance weight for an ESG dimension j , as determined in the survey by the survey taker.

This process is repeated for each PPP dimension, resulting in comprehensive Twin Transition maturity scores.

5.4.3. Next-steps: recommending digital technologies to improve ESG

Based on the company's assessed maturity score, specific digital manufacturing technologies will be recommended to optimize their ESRS impact. The full recommendation is structured in the following way.

The process dimension forms the foundation for technology recommendations rather than the people or policy dimensions. This choice reflects the direct relationship between processes and technology implementation. The process dimension addresses which technologies are deployed and how they operate within the organization. The people and policy dimensions serve supporting roles in this framework. The people dimension encompasses employee knowledge levels regarding technology applications and knowledge-sharing practices. The policy dimension covers how corporate strategy departments facilitate digital technology implementation for sustainability goals. While both dimensions are important for maximizing technology benefits, the process dimension takes priority for advancing Twin Transition maturity levels.

Technology recommendations target the next maturity level above the company's current score. All technologies capable of contributing to specific ESRS impacts are identified and explained for this target level. The technology selection draws from Table D.10 in Appendix D.4. This approach supports informed decision-making rather than prescribing specific solutions. Companies receive a comprehensive overview of available technologies and their potential applications for advancing ESRS impact. This overview enables users to select technologies that align with their strategic objectives and organizational circumstances.

Each recommended technology includes an implementation complexity score specific to its ESRS-impact application. These complexity assessments are derived from Table D.14 in Appendix D.6.5. This information helps companies understand the resources and effort required for successful implementation.

Every technology recommendation also includes a comprehensive sustainability trade-off overview. This analysis addresses two critical questions: What negative impacts might this technology have on other ESRS dimensions? What is the net trade-off when a technology generates both positive and negative impacts on the same ESRS impact? These trade-off assessments are based on Table D.12 in Appendix D.6 and Section D.6.4. This comprehensive view enables companies to make informed decisions that consider the full sustainability impact of their technology choices.

5.4.4. Development of the integrated tool

Choice of interface media

Based on internal discussions at the internship company, the decision-support tool was developed as two interconnected components: a survey and a web application. This two-part structure was chosen for practical development reasons and implemented by the researcher.

The survey was created using Microsoft Forms, a platform already in frequent use within Accenture. This ensured a familiar user experience and allowed survey responses to be securely stored within the company's cloud environment.

The web application was selected as the most appropriate format for presenting the tool's maturity assessment and recommendation functionalities. This choice aligned with several structural requirements outlined in Section 4.3. For example, this design allows for the tool to effectively communicate a clear and concise core message (S1), and it can incorporate a hierarchical structure of KPIs (S4). As a result, users can initially view high-level Twin Transition maturity scores and then explore specific sustainability impacts in more detail.

The web application format also offers high flexibility. It supports the integration of survey data, maturity assessment figures, and recommendation content, while enabling intuitive and interactive navigation for users.

Survey design

The survey is designed to guide users through a structured process that connects seamlessly with the web application. Upon starting the survey, users are welcomed by an introductory screen that features a motivational message: "Let's determine your Twin Transition maturity level through a survey." This screen also displays the same image used in the web application, reinforcing a visual link between the two components.

Next, users receive a brief explanation of the Twin Transition concept and how the survey integrates relevant sustainability themes through the European Sustainability Reporting Standards (ESRS) impacts. This section outlines the survey's objective in relation to the maturity assessment and the follow-up steps. It also introduces the overall structure of the survey.

The survey begins by asking users to indicate the importance they assign to the environmental (E), social (S), and governance (G) dimensions. Each ESG dimension is then introduced in more depth, including explanations of how the people, process, and policy dimensions relate to each one. Following each ESG introduction, the relevant ESRS sections for that dimension are presented.

Each ESRS section has a dedicated page in the survey. These pages begin with a short description defining the specific ESRS impact. Users are first asked whether they want to include this impact in their assessment. If included, they are prompted to rate its importance using four categories: slightly

important, moderately important, very important, or essential. Subsequently, users are asked to assess the maturity of that impact along the PPP dimensions, for both their current state and desired future state.

All ESRS impact pages follow the same structure: a decision to include or exclude, an importance rating, and a maturity assessment across the PPP dimensions. This consistent layout is intentionally designed to create a logical 'flow' in the survey, helping users respond efficiently and consistently across all sections. A visual representation of the survey structure is shown in Figure 5.5.

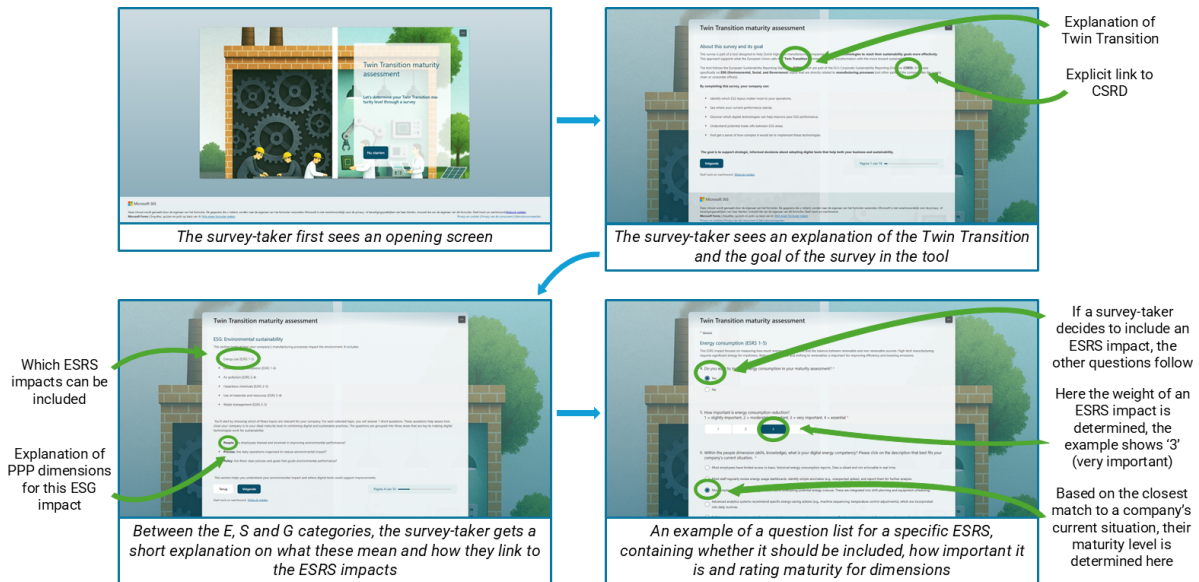


Figure 5.5: Overview of how the three elements of the decision-support tool are interconnected: the survey, the maturity assessment and the next-step overview.

Maturity and next-steps design

The web application is structured around three interactive pages, each playing a specific role in supporting the decision-making process:

1. **Overview page:** This page provides a summary view of Twin Transition maturity. It presents aggregated scores across the people, process, and policy dimensions, highlighting the gaps between current and target scores with a visual representation. The same image shown at the start of the survey is also included here to reinforce continuity and familiarity.
2. **Detailed analysis page:** Users can navigate through the three PPP dimensions using a clickable menu. For each selected dimension, the page displays maturity scores, both current and target, across the environmental, social, and governance categories.
3. **Recommendations page:** Based on the ESRS impacts selected in the survey, this page offers tailored recommendations. When users select a specific ESRS impact, the tool presents relevant technologies that can support progression to the next maturity level. Each technology is accompanied by a short explanation of its contribution and an indication of implementation complexity. Users can also explore trade-offs within the same impact and across different ESG dimensions. Any potential negative effects on other ESRS areas are clearly indicated through a trade-off button.

An overview of these three pages and their features is shown in Figure 5.6. The web application was developed using the Cursor platform, with Python as the primary programming language and Streamlit as the framework for building the interactive interface. The tool is publicly accessible at: <https://twin-transition-tool.streamlit.app/>.

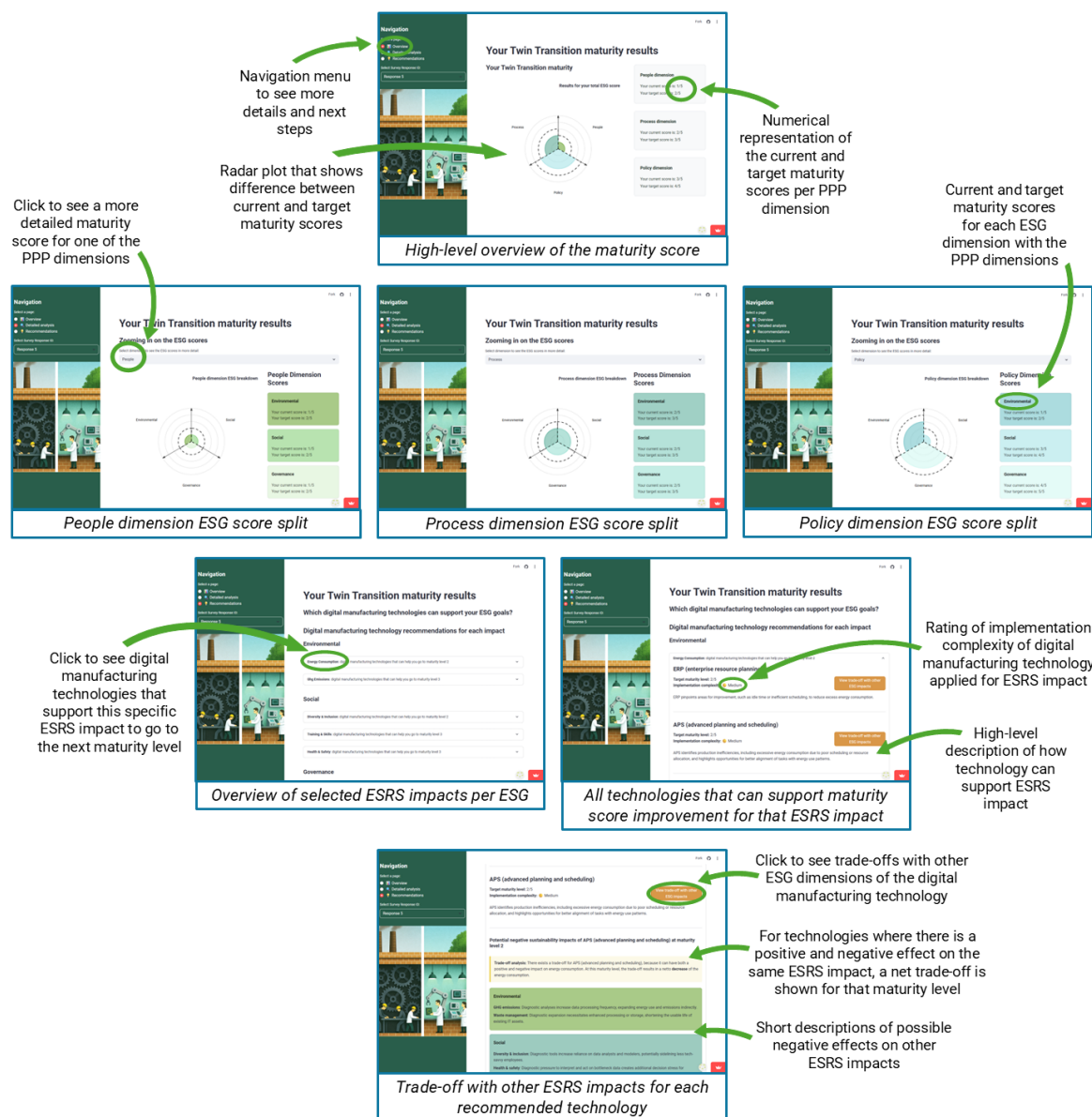


Figure 5.6: Overview of how the three elements of the decision-support tool are interconnected: the survey, the maturity assessment and the next-step overview.

5.5. Phase 3 summary

Sub-research question	What is the corresponding decision-support tool that integrates the identified requirements to support Dutch high-tech manufacturing companies in implementing the Twin Transition?
Selection of a foundational model	•A review of academic and consultancy models led to the selection of the Accenture Industry Sustainability Maturity Model: a practice-based framework well-suited to manufacturing needs. •The model was then systematically reviewed using De Bruin's (2005) method for developing maturity models.
Maturity model dimensions	•Sustainability: ESG (environmental, social, governance) •Implementation and digital: PPP (people, process, policy)
Maturity model sub-dimension selection	•Relevant ESRS impacts were selected in line with the CSRD, as legislation and regulation are key sustainability drivers for Dutch high-tech manufacturing companies. •A materiality assessment was conducted using EIOA for environmental impacts and the MSCI ESG Materiality Map for social and governance aspects. •Relevant digital manufacturing technologies were identified along with their potential to influence selected ESRS impacts. Two interviews were held to validate these links. •The final selection focused on ESRS impacts that are both material for sustainability and addressable through digital manufacturing, this intersection defines the Twin Transition.
Maturity model level definition	•A targeted literature review was conducted on digital maturity levels. •By adapting this with data analytics frameworks, aligned with the Twin Transition's emphasis on effective data use, five levels were defined: descriptive, diagnostic, predictive, prescriptive, and adaptive.
Populating the maturity model	•Digital manufacturing technologies were defined across the five maturity levels. •For each level, their potential to support sustainability was also specified.
Definition of maturity KPIs	•Kibira et al. (2018) was used to guide the bottom-up indicator selection method. •KPIs were defined for each ESRS impact, along with aggregated ESG scores for each PPP dimension.
Next-step: trade-off	•Potential negative ESRS impacts of digital manufacturing technologies were identified at each of the five maturity levels. •For each level, trade-offs were assessed per ESRS impact to determine whether the net effect was positive or negative.
Next-step: implementation complexity	•Based on interviews, ROI was replaced with relative implementation complexity. •Each technology was rated, per maturity level and ESRS impact, as low, medium, or high, based on typical application and its influence on the business dimension of manufacturing.
Tool integration and design	•Survey: MS Forms was used to gather company priorities and assess maturity scores. •Web app: built with Streamlit and Cursor, offering an overview of maturity scores and tailored recommendations.
Chapter results	•The tool integrates company priorities, Twin Transition maturity, and company goals in a structured, evidence-based, and sector-specific way. •Key features: •Sector-specific ESG sub-dimensions aligned with CSRD/ESRS. •Twin Transition maturity model using data analytics-based levels. •Three-tier KPI system for tracking progress. •Digital technology recommendations engine with trade-offs and complexity analysis. •Interactive interface facilitating manufacturing-sustainability discussions.

6

Phase 4: Demonstration & evaluation

Once the decision-support tool has been designed, it is important to test it in practice and assess how well it addresses the defined requirements. In the design science research methodology described by Johannesson and Perjons (2014), this is captured in two sequential phases: *demonstration* and *evaluation*. Demonstration focuses on applying the artifact in a relevant setting to observe its behavior, while evaluation determines the extent to which it fulfills its intended purpose and meets the established requirements.

Due to time limitations, these two phases were integrated into a single step. The tool was demonstrated in a real-world context, and feedback was gathered in parallel to assess its performance, usability, and potential for improvement.

Accordingly, this chapter addresses two sub-research questions:

- **Sub-research question 4:** *How does the integrated decision-support tool for the Dutch high-tech manufacturing sector perform when demonstrated to intended target users?*
- **Sub-research question 5:** *How can the proposed decision-support tool be improved, based on the results of the demonstration phase?*

This chapter presents the main evaluation findings. It starts by briefly explaining the demonstration setup and the context in which the tool was tested. Then, it discusses how participants assessed the tool against the Phase 2 requirements, based on their walkthrough and feedback. Finally, the evaluation is complemented by a second perspective using the 5E framework, which highlights broader qualities of the tool and leads to a set of targeted recommendations for improvement.

6.1. Approach

The decision-support tool was evaluated through a series of supervised survey interviews, as outlined in Section 2.3.6. This method enabled both practical testing and structured assessment within the time constraints of the thesis. It allowed participants to interact directly with the tool while systematically evaluating how well it fulfilled the requirements defined in Phase 2. The evaluation also formed the basis for gathering qualitative feedback on usability, relevance, and areas for further improvement.

The supervised survey focused on systematically assessing how well the tool fulfilled the functional, structural, and contextual requirements established in Phase 2. Participants evaluated each requirement using a three-point rating scale ('not fulfilled', 'partially fulfilled', 'fully fulfilled'), providing clear metrics for performance assessment. This structured approach enabled identification of both successfully implemented features and areas requiring improvement, directly addressing the research questions about tool performance and enhancement opportunities. The full supervised survey interview protocol can be found in Appendix E.1.1.

6.1.1. Participants and interview details

All interview participants matched the intended user profile defined in Section 4.1.3. They were selected to represent diverse professional backgrounds, ensuring that the feedback covered both strategic and operational aspects of the tool. Table 6.1 provides an overview of the participants and the interview formats.

Three interviews were conducted with consultants from Accenture (C1, C4, and C5). While all three work with clients in high-tech sectors, their areas of expertise differ. C1 and C4 focus more on manufacturing and digital technology implementation, while C5 brings expertise in sustainability strategy and ESG performance. Their familiarity with different high-tech sub-sectors and their varying experience levels in sustainability topics ensured a broad evaluation of the tool's features.

The remaining interview was conducted with C2 and C3 from a Dutch manufacturing company. While their company is not considered part of the high-tech manufacturing sector, it produces thermodynamic products for both consumer and industrial applications. At this stage of the research, high-tech manufacturers were not available for interviews, but it was still deemed important to include a company-side perspective alongside consultancy input.

C2 and C3 participated in a duo interview to reflect the tool's aim of bridging sustainability and manufacturing perspectives. C2 represented the technical and digital manufacturing side, while C3 brought the corporate sustainability viewpoint. Their combined input allowed for a focused evaluation of whether the tool could indeed connect these traditionally separate domains, as envisioned in the tool's design (see Chapter 4).

Table 6.1: Anonymized overview of interview participants and their professional background, as well as the interview format.

Identifier	Role and experience	Interview format
C1	Interviewee C1 is a supply chain and manufacturing consultancy leader with over 18 years of experience driving global transformation programs at the internship company. They specialize in end-to-end process design, IT/OT integration, and digital innovation to unlock business value. Key clients they worked with included Dutch high-tech manufacturers in the semiconductor industry.	Survey walkthrough during the interview, half hour interview.
C2	Interviewee C2 is a manufacturing and operations leader with deep expertise in driving process standardization and system harmonization across operations. At [the manufacturing company], they lead the implementation of the global manufacturing. Their focus includes SAP S/4HANA, PLM, MES, and Lean principles to establish a standardized and sustainable way of working across all group plants.	Survey sent and filled in beforehand, one hour interview. Duo interview with C3.
C3	Interviewee C3 is a corporate sustainability leader with over 18 years of experience developing and implementing ESG strategies in multiple industries, now at [the manufacturing company]. They specialize in environmental regulation, stakeholder engagement, and ESG reporting. Their work integrates legal expertise, business strategy, and a commitment to driving sustainable impact.	Survey sent and filled in beforehand, one hour interview. Duo interview with C2.
C4	C4 is a senior manufacturing IT consultancy expert with over 20 years of experience across multiple sectors, including high-tech semiconductor. At the internship company, C4 leads digital transformation initiatives with a focus on MES, IoT, and IT/OT integration. C4 has delivered large-scale MES programs for clients, manages strategic partnerships with key technology providers, and conducts on-site manufacturing assessments to identify opportunities for performance improvement and operational excellence.	Survey sent and filled in beforehand, one hour interview.
C5	Interviewee C5 is a consultancy leader with a PhD in Sustainability Management and a Master's in International Management. They have a demonstrated history in management consulting, specializing in leading circularity and sustainability strategy projects for global companies, including a MedTech company. Their expertise includes the design and implementation of circular business models, partnerships, circular strategies/targets, ESG data and performance management, and ESG (reporting) operating models.	Survey walkthrough during the interview, half hour interview.

6.1.2. Data processing

The evaluation data was processed using thematic analysis following the same methodology applied in Phase 2, as described in Section 2.3.6. The analysis focused on two primary outcomes: systematic assessment of requirement fulfillment and identification of improvement opportunities. Participant

feedback was coded and categorized to reveal patterns in both quantitative ratings and qualitative reasoning.

To ensure accuracy and validation, individual summaries were prepared for each participant and shared for feedback confirmation, these are included in Appendix E.1.2. This checking process verified the interpretation of responses while maintaining participant anonymity. The analysis results inform both the evaluation of current tool performance and the development of targeted recommendations for enhancement.

6.2. Evaluation results through comparison to Phase 2 requirements

Overall, the decision-support tool was rated as most successful in creating clarity, enabling structured conversations, and supporting strategic reflection, while it was rated less favorably in areas that depend on detailed data availability or sector-wide comparability, such as benchmarking and ROI calculation (as these were also both not part of the final design anymore). Figure 6.1 shows an overview of the rating of how well the requirements are fulfilled according to the participants and this section discusses the main patterns and insights that emerged from the interview data to contextualize these survey results.

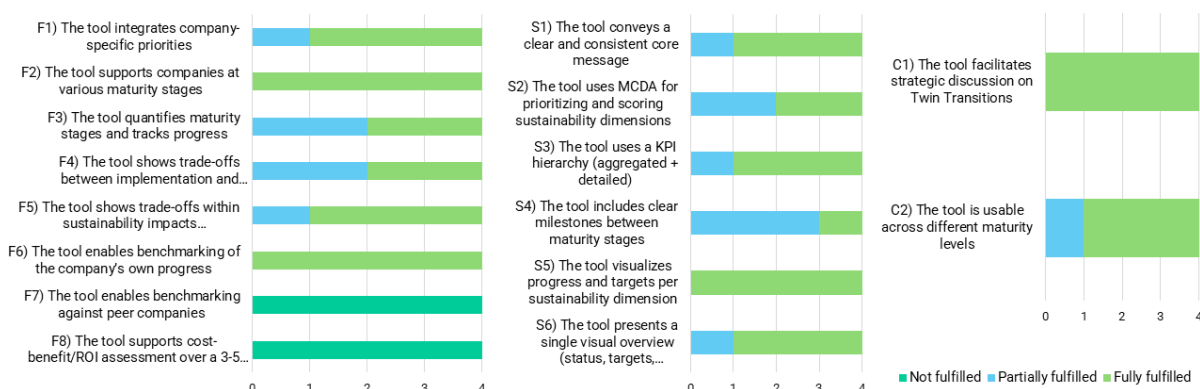


Figure 6.1: Overview of the number of participants that rated each of the functional (left), the structural (middle) and contextual requirements (right) not fulfilled, partially fulfilled or fully fulfilled.

Functional requirements

In terms of functional requirements, the most positively received aspects were those supporting internal prioritization and self-assessment. All participants agreed that the tool effectively enabled companies to benchmark their own progress over time (F3, F6), with C5 confirming, “Yes, that works.” C2 appreciated how this tracking could help motivate technical staff and support accountability: “Many of our technicians would really like that, a kind of maturity measurement: ‘Oh, look, this is how far we’ve come.’” Related to this, the tool’s ability to adapt to different digital maturity levels (F2) was widely praised. C1 noted its capacity to “support users at varying digital maturity levels,” while C2 remarked that “Yes, if I look at the questions, there is indeed a nice spread,” acknowledging how the tool accommodates both mature and less digitally advanced environments.

Another highly valued function was the tool’s support for integrating company-specific priorities (F1). The ability to select relevant ESG themes at the beginning of the survey was seen as an effective customization feature. As C1 put it, “I do think it meets that need, yes. That’s definitely in there.” C5 confirmed this view, stating: “Yes, it fulfilled that. The ESG selection in the survey lets you tailor it to your own priorities.” Participants also responded positively to the tool’s visualization of trade-offs within ESG dimensions (F5). C3 found the integration of environmental, social, and governance elements helpful for framing decisions, saying: “Yes, that’s right. You’ve included ESG, so you’re not just looking at one component. This also shows the trade-offs. That works well.” C1 added: “I do see clear trade-offs... you incur costs from an environmental perspective, but you also have benefits.”

However, functional areas tied to external comparison and financial justification were consistently rated as not fulfilled (F7, F8), though participants’ reasoning reflected their professional contexts. C2, a manufacturing specialist within an industrial company, questioned its real-world feasibility given the operational diversity between firms: “The question is: against whom do you benchmark then? You want

to be able to compare yourself, but with a comparable company.” Their perspective reflects a grounded concern with day-to-day differences in production lines, machinery, and digital maturity across factories. C4, a consultancy expert in manufacturing IT and digital transformation, echoed this skepticism from a broader industry perspective. Having worked with numerous high-tech clients, they dismissed benchmarking as a “consultancy hobby, but rarely truly meaningful,” emphasizing the deep variability between production environments that renders direct comparisons unreliable. Meanwhile, C5, a sustainability strategy manager with a focus on ESG systems and long-term transformation, acknowledged the absence of peer benchmarking but highlighted its future potential. From their strategic point, C5 viewed benchmarking as a potential motivator for industry-wide participation: “That kind of feedback loop would motivate companies to take part, and to share their data in the first place.” This difference in perspectives shows how professional backgrounds may shape how a tool’s feature value is perceived. For leaders in manufacturing operations (C2) and manufacturing IT consulting (C4), the main purpose of the tool may be to support operational excellence. Because of this, they may see peer benchmarking as less useful, since it is often very difficult in practice to find truly comparable firms. From their point of view, manufacturing sites differ too much from each other, so this feature might not work well. On the other hand, for a leader in sustainability consulting, the goal is sustainability transformation, so they may view the same feature differently. For them, benchmarking could help motivate industry-wide data sharing and support broader systemic change. From this perspective, benchmarking is not just a measurement tool but may be part of the solution itself, creating feedback loops and transparency that encourage companies to take part. This difference in how the problem is seen may help explain why the same feature could be viewed as both an unnecessary extra and a key way to motivate change in the future.

Cost-benefit analysis and ROI assessment faced similar critique. C2 raised concrete concerns: “Nice systems, but a SCADA implementation costs about five hundred thousand. We get data and some tools in return, but I wonder: does it demonstrably yield anything for energy or sustainability?” C4 stressed the systemic complexity of ROI calculations in manufacturing: “ROI is not simple in this industry. It’s not as direct as in other sectors.” C5 echoed this difficulty and found the omission understandable: “No, not really.” Even though the need for these features was acknowledged, there was broad agreement that their practical inclusion would require much more context-specific data than the current tool can support. Therefore, this suggests that choosing implementation complexity, based on the Phase 3 interviews, has been the right decision instead of relying on an ROI estimation.

Participants were also somewhat divided on the tool’s ability to recommend digital manufacturing technologies and their implementation complexity (F4). C1 found these descriptions too high-level, particularly given their deep technical expertise. They emphasized the need for more practical and detailed implementation insight, noting: “You would actually want a more in-depth text than this... What exactly does a digital twin do?” and “For example, what can you actually do with a control tower?” In contrast, C2 was more positive about the level of explanation provided and found the tool’s framing of sustainability impacts helpful in sparking internal awareness: “Yes, that confirms what you intuitively suspect.”

Regarding the implementation complexity scores associated with different technologies, both C4 and C5 expressed that these were too superficial. C4, a consultant with extensive experience in deploying MES and IoT solutions across diverse industrial contexts, noted: “The content is good, but the presentation could be more visual,” and emphasized that the complexity dimension needed more depth: “I missed that a bit: why is something difficult? That SPC is difficult because you need high-quality data and algorithms at a certain level, that helps the user understand what it means.” C5 echoed this view, suggesting that including justifications alongside complexity ratings would improve interpretability: “I would be interested in that as a company, or maybe you could include a link to more details.” These critiques underscore a shared concern among participants with technical or strategic implementation experience: while the tool initiates the right conversations, its outputs must be underpinned by more nuance and specificity to better support decision-making.

Structural requirements

Structurally, the tool was perceived as robust and well-structured. The clarity of the survey, its logical flow, and the intuitive design of the maturity model were commonly praised. C4 found the experience engaging: “I found the survey clear and pleasant to fill out,” and added, “After three or four questions, I really got into a flow.” C2 emphasized that completing the survey itself had already triggered reflection

and helped identify internal gaps: “At such a moment, I thought: ‘Oh yes, we don’t actually have this yet.’ Then you realize: if we find this important, we need to start working on it. That awareness helps tremendously.” This highlights how the structural clarity of the survey not only supports usability but also serves as a diagnostic prompt in itself (S1). C1, with experience in end-to-end digital manufacturing systems, appreciated the structure and flexibility of the tool (S1, S5), stating: “The tool enables customization across ESG dimensions and supports users at varying digital maturity levels. ‘I do think it meets that need, yes. That’s definitely in there.’” C5 similarly valued the survey’s structure as a strategic orientation mechanism: “The tool can start the discussion.”

The overall dashboard and visual layout were received positively, though one important suggestion for improvement came from C4, who noted the lack of an immediate summary output (S6): “What I missed most was really that one-pager. Afterwards, I noticed: okay, I filled everything in, but what now? What are the conclusions?” This highlights a gap between the structured input process and the clarity of the outcome presentation. Another structural area where fulfillment was partial was in the communication of maturity stage transitions. While participants could generally understand their company’s current position, most agreed that clearer indicators of milestones between maturity levels would improve the tool’s usability. This lack of explicit thresholds made it harder to understand what specific actions would be needed to progress from one level to the next.

Contextual requirements

In terms of contextual requirements, the tool’s performance was rated the highest overall. Its ability to facilitate strategic discussions, particularly across siloed domains like sustainability and operations (C1), was repeatedly highlighted as one of its key strengths. C2 and C3, who were intentionally interviewed together to test this bridging function, found that the tool successfully provided a common language. C3 stated: “If you have conversations without such a framework, you speak different languages so to say. This creates common ground.” They also pointed out a concrete use-case for the tool within their company context: C2 explained that the tool’s output, such as the maturity measurement report, could be particularly relevant for senior leadership discussions, especially with their CTO: “C3, if you go to the management board with this (for example, to the CTO) they would really like to see these kinds of insights.” They saw the tool not only as a way to facilitate internal dialogue between departments, but also as a way to communicate progress and gaps to leadership and build momentum across multiple manufacturing sites.

The consultants echoed these sentiments. C1 saw the tool as a useful aid in early-stage client discussions: “If you can clearly present the benefits purely from a sustainability perspective in one tool, then that really does have value.” C5 also mentioned that the tool can be a conversation starter. C4 agreed, stating: “What you’ve developed here is an initial inventory. The starting point for the conversation.” They see it being used to “create urgency” by visually highlighting where a company stands and where its biggest gaps lie. According to C4, the tool serves as a “stepping stone” that helps identify priorities and frame discussions with stakeholders like plant managers or corporate leadership.

6.3. Evaluation through comparison to 5E requirements

In addition to assessing how the decision-support tool meets the design criteria derived from the identified challenges, it is also valuable to evaluate the tool through the lens of the 5E framework: efficacy, efficiency, effectiveness, elegance, and ethicality. This framework, introduced by Checkland and Scholes (1990) and referenced in the design science research literature by Johannesson and Perjons (2014), offers a high-level yet focused set of qualities that help characterize an artifact’s performance in practice.

While the design criteria provide a tailored and challenge-specific basis for evaluation, ensuring that the tool addresses the specific needs, constraints, and objectives that emerged during the design process, the 5E framework contributes a complementary, more generalized lens. As Johannesson and Perjons note, although design science research benefits from a broad range of artifact qualities, having access to a concise and universally applicable set of evaluation dimensions like the 5Es can enhance clarity and comparability across different contexts. Therefore, this dual approach strengthens the rigor of the evaluation. It ensures not only that the tool responds to the original challenges identified in Chapter 3, but also that it adheres to more generalizable standards of quality that are important for adoption and long-term use.

In this context, the 5Es definition from Johannesson and Perjons (2014) can be interpreted as:

- **Efficacy:** The extent to which the tool delivers its intended sustainability insights and recommendations under ideal usage conditions.
- **Efficiency:** The degree to which the tool achieves its intended outcomes with minimal resource consumption, such as time, effort, or costs. A tool is efficient if it enables actionable insights without requiring extensive manual input, complex interpretation, or large-scale data processing.
- **Effectiveness:** The extent to which the tool generates meaningful sustainability outcomes in real-world use, considering the variability of organizational contexts (e.g., differing digital maturity or data availability).
- **Elegance:** The extent to which the tool is intuitively designed, visually coherent, and enjoyable to interact with. A tool is elegant if its interface, structure, and outputs feel well-integrated and easy to understand for both technical and non-technical users.
- **Ethicality:** The extent to which the tool and its recommendations align with ethical principles, such as fairness, inclusiveness, transparency, and environmental and social responsibility.

Table E.1 in Appendix E identifies how, based on the interviews, each interview participant would rate each of the 5E dimensions. Overall, the 5E-framework evaluation interviews offer a consistent narrative: the decision-support tool succeeds in sparking the right conversations but has limitations when it comes to operational precision. Across all participant types, consultants, manufacturing experts and sustainability strategists, the tool's initial value was quickly clear. The survey prompted self-reflection, the dashboards highlighted blind spots, and the ESG framing supported cross-functional conversations. In this respect, the tool achieves its foundational purpose: it provides a common ground for bridging digital manufacturing and sustainability, domains that are often siloed within organizations.

Participants' feedback diverged when it came to what follows after that initial purpose. Several participants noted a steep jump from high-level insights to plant-floor application. Without access to site-specific context, ROI information or benchmarking against industry peers, the tool's outputs remain more directional than actionable. This concern was particularly strong among users with deep manufacturing expertise. As one example, C2 described managing a factory where modern PLCs operate alongside 1960s machinery, highlighting how the survey can feel both realistic and aspirational depending on the site. The tool's generic design creates tension in such heterogeneous environments: it might perform well under ideal conditions, but its utility could be lower when faced with real-world complexity.

Despite these limitations, the tool's core strength, facilitating strategic conversations, is repeatedly affirmed. Participants described it as a "first-step conversation starter" (C5) and "a way to see that technology can really help us" (C2). The tool effectively translates abstract Twin Transition goals into tangible questions for companies to consider. However, when users sought more technical depth, such as detailed explanations of specific technologies or compatibility with existing ERP systems, the tool's limitations became apparent. As C1 noted, the tool provides a framework but not the functional detail required for implementation planning.

One of the most illuminating findings relates to user expectations around usability and explanation. Participants appreciated the visual structure and clarity of the dashboard but called for more explanatory content, such as clearer definitions and a simplified one-page summary. For these users, "elegance" was not defined by aesthetics but by accessibility. As C3 asked, "What does a maturity score really mean?", suggesting that explanatory clarity is essential for turning awareness into action. The tool demonstrates functional elegance by creating common ground, but falls short of delivering the explanatory elegance needed for use without the researcher's presence.

Interestingly, concerns about bias, greenwashing, or opaque algorithms were absent. Participants appeared to find the inclusion of ESG dimensions sufficient to establish ethical legitimacy at the prototype stage. This suggests that, for now, transparency of scope, what the tool includes, is more important to users than transparency of computation, or how exactly recommendations are generated.

Applying the 5E framework reveals that the tool's greatest strength and its main limitation stem from the same source: its ambitious breadth. It attempts to connect digital and sustainability domains, serve both mature and less digitized factories, and provide high-level guidance alongside actionable insight. This scope enables wide applicability but necessarily limits depth. Rather than being a prescriptive decision-making system, the tool encourages users to think systematically about relationships between

digitalisation and sustainability they may not have previously considered. Its value lies not in offering definitive answers but in helping organizations ask better, more informed questions about the Twin Transition.

6.4. Recommendations for improvement

The evaluation of the decision-support tool using the 5E framework, along with the interviewees' suggestions about requirements they felt were not fully met during the demonstration, provides several clear and targeted recommendations. Overall, these recommendations do not suggest a full redesign of the tool's core structure but instead point to improvements that can make it clearer, more context-sensitive, and easier to use in practice.

Efficacy

While the tool successfully maps digital manufacturing technologies to sustainability impacts, users noted that the descriptions often lacked technical specificity. To improve clarity and trust in the recommendations, the descriptions of each digital technology should be expanded to include more extensive and accurate explanations of how the technology contributes to ESG improvements under ideal usage conditions. Additionally, a brief context-setting question section at the start of the survey could help tailor recommendations based on local realities, such as data availability, system integration levels, or equipment age. This would allow the tool to distinguish between directional insights (useful for initial awareness) and actionable guidance (applicable when enabling conditions are met), ensuring users interpret the results appropriately.

Efficiency

Participants highlighted opportunities to streamline the user experience and reduce the cognitive effort required to interpret results. One area of improvement is the explanation of implementation complexity ratings. Short, contextual tooltips could clarify why a given technology is rated as low, medium, or high complexity, making the tool easier to navigate for less technical users. Furthermore, distinguishing between foundational technologies, those offering clear, low-risk sustainability value, and more aspirational or experimental solutions would help users prioritize actions effectively. Integrating the currently separate survey and dashboard into a unified platform would further improve the workflow. Finally, integrating the survey and the web application could improve the user experience.

Effectiveness

The tool's effectiveness could be strengthened by better reflecting the realities of varied organizational maturity. Several users pointed out that even the lowest answer options in the survey sometimes assumed capabilities or data infrastructure that were not present. To address this, the tool should include a "level zero" option that allows companies to indicate the complete absence of a certain maturity dimension. In addition, clearer definitions of each maturity score would help users understand what a given score represents and what is required to move to the next level. For companies operating multiple sites with different levels of digital transformation, the ability to assess each factory separately, would help maintain the accuracy and relevance of the results. To further support improvement planning, the tool should highlight which ESG areas score lowest or are not yet addressed, providing a direct link between the assessment outcomes and the ESRS materiality framework.

Elegance

The tool's logical structure and content were well received, but the survey's visual presentation was seen as overly text-heavy. Participants called for a more visual and accessible design that reduces cognitive load and enhances comprehension. A cleaner layout, supported by infographics, icons, and call-out boxes, would improve the readability of both the survey and the results. For the web application, explanatory clarity emerged as a key dimension of perceived elegance. Visual aids that are accompanied by plain-language explanations would help users better interpret their position and progress.

Ethicality

Finally, while participants did not express strong concerns about greenwashing or algorithmic opacity, one flagged the potential for socially desirable responses, particularly in the sustainability-related

sections. To address this, the tool could incorporate reworded control questions to check for consistency in user input. The addition of a level-zero response option would also support more honest self-assessment by allowing users to acknowledge the absence of data or capability without penalty. Overall, users appeared to value transparency of scope more than transparency of computation at this stage of tool development.

6.5. Phase 4 summary

Sub-research question	How does the integrated decision-support tool for the Dutch high-tech manufacturing sector perform when demonstrated?
Sub-research question	How can the proposed decision-support tool be improved, based on the results of the demonstration phase?
Semi-structured interviews with supervised survey	•Conducted 3 interviews with experts from Dutch high-tech manufacturing from a consultancy perspective and 1 duo-interview with a manufacturing and a sustainability expert from a Dutch manufacturing company. •2/5 interviewees filled in the maturity survey beforehand, so they could see their personalized decision-support dashboard. •Interview sessions included a live walkthrough of the web-based decision-support tool. •Participants assessed the tool using the requirements defined in Phase 2.
Application of the 5E framework	•Application of the 5E framework (efficacy, efficiency, effectiveness, elegance, ethicality) per participant and to the total interview results to have a second evaluation lens on the decision-support tool.
Chapter results	•Identification of the decision-support tool use-case: facilitation of structured discussions between sustainability and manufacturing stakeholders. •Identification of tool strengths: enable internal reflection & prioritization, customizable ESG focus, clear maturity model structure and overview of holistic positive & negative impacts. •Identification of improvement areas: integration of maturity assessment & results into one tool, deeper digital manufacturing technology implementation descriptions and integration of ROI & peer benchmarking features

7.1. Contributions of this research

7.1.1. Scientific contributions

Addressing the limited literature landscape

The literature review in Chapter 1 highlights that Twin Transition research remains an emerging and still limited research field. As the bibliometric analysis by Fatemi et al. (2025) shows, the concept of the Twin Transition has only recently gained academic traction. Researchers still use terms like "twin transition" and "twin transformation" interchangeably, reflecting the field's early stage of theoretical development. This lack of established literature mirrors the recency of the concept itself: the European Union introduced the Twin Transition framework only a few years back, driven by the urgent need to advance digitalization and sustainability in parallel (Muench et al., 2022).

To date, only a small number of studies attempt to capture the "twin" interaction between digital transformation and sustainability, and these have clear limitations, as outlined in Chapter 1. High-level capability frameworks, such as Christmann et al. (2024), often outline what organizations could achieve but do not provide practical guidance on how to do so. Other models, like Meuser et al. (2024), take a narrow approach by focusing only on direct emissions (Scope 1 and 2), overlooking the broader Environmental, Social, and Governance (ESG) dimensions that modern sustainability standards require.

This thesis addresses these gaps by providing a more comprehensive and operational framework. Unlike previous models, the decision-support tool developed here explicitly integrates the full ESG scope demanded by legislative frameworks like the Corporate Sustainability Reporting Directive (CSRD). The tool assesses a wide range of sustainability impacts, from energy use and emissions to workforce diversity and governance, while offering both a maturity assessment and concrete pathways for progress. In this way, it moves beyond the binary treatment often seen in existing literature, where digital and sustainability transformations are studied either in isolation or only superficially linked. Instead, it contains real integration points where digital technologies directly shape sustainability outcomes.

Perhaps most importantly, this research closes the actionability gap identified in the literature review. While many existing models stop at high-level recommendations, this study delivers a decision-support tool that is ready for practical use. It combines three elements: (1) a survey for assessing an organization's current state, (2) a maturity model for visualizing gaps, and (3) a recommendation module for selecting relevant technologies. Together, these components help companies identify both the positive and negative sustainability impacts of digital solutions, tackling the trade-off challenge highlighted in Chapter 1. The demonstration sessions in Chapter 6 confirm the tool's practical value, while also pointing to areas where it can be refined further.

A key insight from the literature analysis in Chapter 1, was the clear disconnect between macro-level policy frameworks and micro-level implementation realities. Much of the existing Twin Transition research remains either at the macro-level (exploring policy contexts and broad transformation pathways) or dives deep into specific technologies without linking them back to bigger systemic questions. This thesis bridges that gap by creating a clear connection from high-level drivers to day-to-day, factory-

floor decisions in the following way:

- At the **macro-level**, the research aligns with European policy initiatives such as the European Green Deal and the CSRD, situating the work within the broader strategic and regulatory context.
- At the **meso-level**, these policy pressures are translated into concrete implementation challenges, sector-specific material impacts (mapped to ESRS topics), and relevant digital technologies tailored to Dutch high-tech manufacturing.
- At the **micro-level**, the decision-support tool links specific digital technologies (such as ERP systems, SCADA, and digital twins) to their detailed, measurable effects on ESG sub-dimensions, covering both benefits and trade-offs.

This multi-level integration creates a clear analytical bridge that connects ambitious policy goals with the practical decisions managers, engineers, and strategists must make. In doing so, the research provides a concrete method for translating high-level ambitions into operational actions.

Additionally, this thesis contributes sector-specific insights that have been largely missing from existing Twin Transition literature. Recognizing that implementation challenges differ per sector, this research focuses on the Dutch high-tech manufacturing industry. The study triangulated academic literature to establish the theoretical base, grey literature to capture recent practice, and semi-structured interviews to ground findings in real-world constraints. This combined approach ensures the resulting decision-support tool is not only academically robust but also practically relevant.

- **Phase 1** delivered the first consolidated Twin Transition challenge overview for this sector, drawing on an extensive literature review and eight expert interviews. This resulted in ten core challenges, four of which were prioritized using the Stacey Matrix, providing a starting point for both researchers and practitioners.
- **Phase 2** translated these challenges into functional, structural, and contextual requirements. Using MoSCoW prioritization in five user interviews, the research defined what “actionable” could mean in practice.
- **Phase 3** embedded this sector knowledge into a new Twin Transition maturity model. ESG sub-dimensions were selected using EEIOA and MSCI materiality mapping, while five levels of digital maturity were detailed with concrete technologies and their associated sustainability impacts. The EEIOA provided, to the author’s knowledge, the first production-based sector “x-ray” of Dutch high-tech manufacturing. By reconstructing the sector from EXIOBASE-3 industries weighted by GDP share (Velthuisen et al., 2024), the analysis quantified previously unaggregated impacts. Notably, it revealed that hydrofluorocarbons (HFCs) are a more significant emission source than CO₂ for this sector, making it the Netherlands’ eighth-largest industrial HFC emitter, an insight that challenges the industry’s low-emission image. These patterns help refine the ESRS topics most relevant for this sector (e.g., E2-4 pollution, E5-4 resource use).
- **Phase 4** confirmed the practical relevance of the final tool. All four demonstration sessions showed that it helps bridge the “awareness-to-action” gap by creating a shared language between sustainability, IT, and operations teams and by highlighting trade-offs that often remain invisible.

Finally, this research makes an important contribution to the field of Industrial Ecology by offering a more detailed socio-technical perspective on how digital transformation and sustainability interact within advanced industrial systems. Industrial Ecology, which examines the systemic connections between society, the economy, and the natural environment (International Society for Industrial Ecology, 2024), has long focused on quantifying and improving the efficiency of material and energy flows (Han et al., 2021). Established methods like Life Cycle Assessment and Material Flow Analysis have played a key role in promoting eco-efficiency and circular economy strategies.

However, this study argues that the quick digital transformation of manufacturing requires the field to expand its traditional focus. Digital technologies are not simply add-ons to existing industrial processes: they fundamentally reshape the relationships that Industrial Ecology seeks to understand.

This thesis advances the field by moving beyond a purely technical or physical analysis. It introduces a framework that explicitly connects the social (People), technical (Process), and governance (Policy) aspects of digital manufacturing to their sustainability effects. By bringing these dimensions together, this research helps broaden Industrial Ecology’s traditional lens from viewing industries mainly as physical metabolisms to recognizing them as hybrid systems where digital layers create new opportunities

and new impacts (Han et al., 2021).

This more integrated perspective makes it clear that digital technologies are not passive tools for improving established processes. Instead, they act as transformative elements that create new industrial-ecological dynamics. For example, a digital twin allows a physical process to be modeled virtually, making it possible to experiment and optimize without using physical resources. Yet at the same time, running digital twins demands significant computing power and energy, adding new environmental impacts that must be accounted for. By providing a structured way to examine both the enabling potential and the direct environmental costs of digitalization, this research equips Industrial Ecology with a more robust approach for studying today's complex, interconnected manufacturing systems. In doing so, it encourages the field to evolve in step with the digital realities shaping modern manufacturing (Pauliuk et al., 2022).

Methodological contribution of bridging theory and practice with mixed methods

This research shows how Design Science Research (DSR) can be systematically applied to help close the persistent gap between theory and practice within the Twin Transition literature as outlined in Chapter 1. While previous studies have often highlighted implementation barriers or proposed conceptual models, few have demonstrated the full process: from problem identification through artifact development to real-world validation. By applying a five-phase DSR approach, this thesis offers a concrete methodological pathway for translating Twin Transition research into practical, usable tools for industry.

A key part of this contribution lies in how the study integrates multiple data sources and validation stages throughout the DSR cycle. The combination of a PRISMA-guided literature review, expert interviews, and supervised survey-based evaluation has provided a strong foundation for developing an artifact that is both theoretically robust and practically relevant. This multi-method design responds directly to a recurring weakness in Twin Transition research, as noted in Chapter 1: studies often lack either theoretical depth or practical feasibility, but rarely succeed in combining both.

This research demonstrates how a step-by-step DSR approach can address that challenge in practice:

- **Problem explication:** The study shows how to combine insights from comprehensive literature analysis with expert perspectives to define a problem that is both conceptually grounded and relevant for industry stakeholders.
- **Requirement definition:** It illustrates a clear method for turning broad challenges into concrete functional, structural, and contextual requirements, laying a strong basis for effective design.
- **Design and development:** The research demonstrates how to integrate diverse knowledge domains, such as ESG frameworks, digital maturity models, and technology-impact assessments, into a coherent tool that addresses multiple dimensions of the Twin Transition.
- **Demonstration and evaluation:** It also shows how to validate an artifact systematically against its original requirements by involving intended users directly, generating feedback that strengthens both its design and its practical relevance.

Through this complete application, the thesis highlights DSR's potential for bridging the divide between abstract theory and actionable solutions (Johannesson and Perjons, 2014). It offers a methodological reference point for future studies that aim to develop practical tools for addressing complex, systemic transitions, demonstrating that DSR is not limited to IT artifacts but can also be applied to challenges at the intersection of technology, society, and sustainability.

The research also makes a methodological contribution by combining quantitative impact assessment with qualitative requirement definition. By linking EEIOA-based impact prioritization with stakeholder-driven input, the study shows how mixed-method approaches can strengthen Twin Transition research, ensuring that empirical accuracy and practical utility are addressed side by side.

This integration represents an important step forward compared to previous approaches that either rely on generic sustainability frameworks without sector-specific nuance or depend solely on expert judgment without empirical validation, as outlined in Chapter 1. The approach developed here shows promise for broader application across different manufacturing contexts and national settings. By aligning the method with current regulatory reporting standards, it further ensures that research outputs remain relevant and implementable for industry practice.

Reflection on sustainability contribution from an Industrial Ecology perspective

Digital manufacturing technologies as a socio-technical enabler of sustainability

This research reinforces a key insight: digital manufacturing technologies are not inherently sustainable or unsustainable, their real impact depends on how they are implemented within specific industrial contexts. The sustainability review conducted across varying levels of digital maturity showed that no technology produces purely positive or negative outcomes on its own. Instead, a technology's contribution to sustainability depends on how it is integrated, managed, and used within the broader organizational and operational system.

Viewed through the lens of Industrial Ecology, this finding supports the idea that digital transformation is not simply a technical upgrade, but a socio-technical process (Iapaolo et al., 2024). Sustainability outcomes do not originate automatically from the technology itself but emerge from how it interacts with people, governance structures, and wider economic and regulatory environments.

This study also highlights that reaching meaningful sustainability benefits depends on having a minimum level of digital maturity in place. Companies need reliable, high-quality, real-time data to monitor and steer their ESG performance effectively. From an Industrial Ecology perspective, digital manufacturing systems can be seen as industrial ecosystems with a form of "metabolism": the flows of energy, materials, and emissions that shape their environmental footprint (Han et al., 2021). Technologies such as IIoT and advanced data analytics serve as the sensory system of this metabolism, providing the visibility needed to identify inefficiencies and improvement areas. Without this data-driven foundation, organizations have limited capacity to measure, manage, or improve their sustainability performance in a credible way.

As digital maturity grows, so does the potential to align operations more closely with sustainability goals. Companies that deploy more advanced technologies can optimize processes with greater precision. However, this research also shows that higher levels of digital maturity bring new layers of complexity. Realizing advanced optimizations often requires significant investment in sophisticated tools, such as AI-driven decision-support systems, and may create tensions with other business objectives, particularly where sustainability goals do not fully align with cost efficiency or production targets.

These tensions illustrate a fundamental challenge at the heart of Industrial Ecology: managing industrial systems for multiple, often competing objectives (Han et al., 2021). For example, maximizing energy efficiency may place limits on production capacity or demand trade-offs in cost and flexibility. Addressing such trade-offs requires more than technical tools, it depends on broader organizational alignment, clear governance structures, and employee buy-in. Without this parallel evolution of the social and institutional system, even the most advanced digital solutions are unlikely to deliver their full sustainability potential.

By framing digital technologies as part of a dynamic socio-technical system, this study provides a more realistic and actionable understanding of how digital transformation can support sustainability in high-tech manufacturing. It shifts the question from whether a given technology is sustainable to under what conditions it enables more sustainable outcomes.

The limits of optimization: why efficiency is not enough

This research also clarifies an important boundary to the role that digital technologies can play in supporting sustainability: while digital tools can significantly enhance operational efficiency, they cannot, on their own, deliver comprehensive sustainability outcomes. This inherent limit is visible in the design logic of the decision-support tool itself. By structuring recommendations around digital maturity levels rather than sustainability maturity, the tool explicitly demonstrates the scope (and the boundary) of what digital manufacturing technologies can achieve.

The review of digital technologies' contribution to the ESRS topics illustrates this clearly. These tools excel at delivering efficiency improvements: they reduce energy use per product, optimize material flows, and cut downtime through predictive maintenance. However, these improvements mostly affect the relative impact of production processes. They do not eliminate absolute resource use or emissions altogether. For example, a factory can use digital systems to optimize its energy use, but to meaningfully reduce Scope 2 emissions, companies still need to invest in renewable energy sources, whether through on-site generation or long-term procurement agreements. Digital optimization alone does not substitute for clean energy infrastructure.

This distinction underlines a broader principle well established in Industrial Ecology: while eco-efficiency is valuable, it has clear limits (Hertwich, 2005). Making processes more efficient reduces

environmental impacts per unit produced, but does not automatically reduce overall impacts when production volumes continue to grow. As this research shows, there is a clear point beyond which digital maturity alone cannot deliver full sustainability; deeper structural shifts are needed, in energy systems, supply chains, infrastructure, and business models.

In this sense, the Twin Transition offers powerful tools but also risks reinforcing a form of technological solutionism: the idea that sustainability challenges can be solved purely by pushing digital sophistication further (Iapaolo et al., 2024). By explicitly addressing the limits of this mindset, this research contributes to a more grounded understanding of what digital transformation can realistically deliver for sustainability, and where broader, systemic interventions remain essential.

7.1.2. Contributions to society and practice

Contribution to society

This research offers a meaningful societal contribution by directly engaging with the dual challenges of sustainability and digital transformation within the Dutch high-tech manufacturing sector. A strong, future-oriented high-tech industry is important to the economic resilience of the Netherlands, as this sector contributes significantly to national income, employment, and technological innovation (Velthuis et al., 2024). The way this sector navigates the Twin Transition will be instrumental in determining the country's ability to meet its 2040 sustainability objectives while maintaining its position as a global technology leader.

The decision-support tool developed in this study provides a practical framework for aligning digital innovation with sustainability performance, moving beyond high-level policy discussions. Grounded in the requirements of the CSRD, the tool offers an operational approach for assessing the Environmental, Social, and Governance (ESG) implications of digital manufacturing technologies. In doing so, it supports Dutch high-tech manufacturers in making strategic, evidence-based decisions that not only benefit individual firms but also strengthen the broader industrial ecosystem. By supporting alignment between technological progress and sustainability goals, the tool could contribute to a more resilient and future-proof industrial landscape in the Netherlands.

Opportunities for Dutch high-tech manufacturers and consultants

The findings from the demonstration and evaluation phase highlight several practical implications for how the decision-support tool can be applied by Dutch high-tech manufacturers and the consultants who advise them.

The tool is designed to act as a strategic enabler and “conversation starter” within organizations. By providing a structured basis for reflection and discussion, it bridges gaps between departments, particularly those focused on digital transformation and those responsible for sustainability, and supports more integrated decision-making. Used effectively, it can strengthen internal collaboration while also serving as a structured, evidence-based foundation for external advisory work.

- **Supporting a shared understanding:** The tool creates a common language around the Twin Transition, clarifying how digital technologies connect to concrete ESG goals. Its visualizations of current and target maturity levels across People, Process, and Policy domains help both internal teams and external advisors build a clear, shared picture of where an organization stands and where it aims to progress.
- **Identifying opportunities and blind spots:** Demonstration in Phase 4 showed that the combined survey and web application reveal areas for improvement and overlooked risks. By mapping digital technologies to specific ESG impacts, the tool enables deeper discussion of investment priorities, strategic focus areas, and hidden interdependencies.
- **Structuring strategic dialogue and trade-offs:** The tool does not just present benefits but also makes trade-offs explicit, highlighting potential downsides such as environmental footprints and implementation challenges. This encourages users to look beyond cost or technical feasibility alone and align digital investments more closely with sustainability and business goals. The tool's outputs can be used to guide clients through these complex decisions in a structured, data-informed way.
- **Translating insights into action:** The maturity model and “next-steps” module help turn high-level goals into concrete actions by suggesting relevant digital manufacturing technologies based on ESG priorities and current capability levels. This enables organizations and advisors to co-develop realistic roadmaps and actionable initiatives grounded in shared evidence.

By applying the tool as a flexible framework for reflection, alignment, and planning, high-tech manufacturers and consultants can engage more effectively with the strategic tensions and opportunities of the Twin Transition.

7.2. Generalizability of results

The deliberate scoping choices in this research made it possible to carry out a focused study that balances depth with practical relevance. At the same time, these choices naturally define clear boundaries around how the findings can be generalized. Understanding these boundaries is important for interpreting the research contributions realistically and for identifying where future work might expand or adapt this study's insights. This section outlines how these limitations shape the broader applicability of the decision-support tool, while also pointing to areas where the results may hold value beyond the immediate context.

7.2.1. The trade-off between depth and breadth

The scoping decisions illustrate a common tension in applied sustainability research: the need to balance a comprehensive, system-level understanding with the need to deliver actionable, practical outputs. By narrowing the focus to selected aspects of the Twin Transition, to a specific national and sectoral context, and to a defined organizational profile, the research was able to achieve a level of depth and practical impact that would have been unattainable with a broader scope. However, this depth comes with clear trade-offs that affect how far the findings can be transferred to other contexts.

Sectoral and geographical scope

Focusing on the Dutch high-tech manufacturing sector brings both clear strengths and limitations for wider application. On the one hand, the sector-specific lens makes the findings more detailed and practical than a generic framework would be. For example, the EEIOA analysis revealed that, in this sector, hydrofluorocarbons (HFCs) are a more significant emissions source than CO₂, an insight that would likely have remained hidden in a multi-sector study. This level of specificity enables more precise and targeted action within the sector studied.

On the other hand, this same specificity limits how directly the results can be applied to other manufacturing domains. The environmental priorities identified through the materiality assessment may differ substantially in other sectors. For example, industries with high water consumption or significant particulate emissions would require a different sustainability focus than the priorities reflected in this tool. This suggests that while the core methodological approach is likely transferable, the specific content and recommendations would need significant adaptation to suit other industrial contexts.

Interestingly, the Phase 4 evaluation did include a demonstration with a manufacturing company outside the high-tech sector. This case indicated that the tool was still seen as highly useful in a different setting. Although this single example does not prove broad generalizability, it does suggest that parts of the tool, especially the underlying framework, may be valuable to other manufacturing companies as well.

The geographical focus on the Netherlands also shapes transferability. While the research is grounded in Dutch sector dynamics, the main regulatory driver (the CSRD) operates at the European level. This creates a notable tension: the tool's detailed content and validation are country-specific, but its primary policy driver is supranational. This suggests that the tool's relevance could extend beyond the Netherlands, particularly since many Dutch high-tech companies (such as ASML, Philips, and Thales) operate globally.

At the same time, it is important to note that the tool is closely aligned with Dutch industrial structures, innovation systems, and business practices. These elements may not map directly onto other national contexts, even within Europe, where differences in industrial policy, sustainability governance, and technology adoption can strongly shape how the Twin Transition unfolds in practice (Teixeira and Tavares-Lehmann, 2022).

Organizational scope and scale effects

A further boundary lies in the tool's primary focus on large enterprises. While the tool was not intentionally designed to exclude small and medium-sized enterprises (SMEs), its emphasis on structured frameworks, formal governance processes, and advanced digital technologies reflects the capacities and resources more commonly found in larger organizations.

This raises important questions about how scalable or inclusive the approach is for SMEs. Smaller firms often face very different challenges in pursuing the Twin Transition. Limited investment capacity, restricted technical expertise, and leaner organizational structures can make it more difficult to adopt the kinds of structured, capital-intensive pathways that the tool assumes (Nunes et al., 2012). For instance, advancing through higher levels of digital maturity often requires significant upfront investment and specialized skills, which may be out of reach for many SMEs. Likewise, the governance processes the tool recommends may not align with the informal, flexible ways that smaller companies typically manage change.

Process-centered sustainability

Focusing exclusively on direct manufacturing processes (Scope 1 and 2) enabled this research to draw clear connections between digital technologies and specific sustainability outcomes. However, this process-centered scope also represents an important boundary for how the results could be interpreted. By design, the tool does not address supply chain or full product lifecycle impacts (Scope 3), areas that, in high-tech manufacturing, often account for the majority of sustainability impacts (Ocicka et al., 2022).

The EEIOA results confirm this empirically: most environmental impacts in Dutch high-tech manufacturing occur upstream, particularly during raw material extraction and processing. By leaving these upstream impacts outside its scope, the tool covers only a portion of the total sustainability footprint. From a systems perspective, this creates a risk that process-level improvements alone may lead to decisions that optimize local efficiencies without addressing larger sustainability priorities (Jayal et al., 2010).

This limitation has direct implications for how the tool could be used. While it offers strong guidance for process-level optimization, it cannot deliver a complete roadmap for companies seeking deep, systemic sustainability transformation. Instead, it could be seen as a practical starting point. One that provides operational clarity but must be complemented by broader supply chain and lifecycle considerations.

Twin Transition: emphasis on greening by IT

The definition of the Twin Transition used in this study, "greening of and by IT," following Hellemans and Oostervink (2025), shaped the overall design of the decision-support tool. In practice, however, the final tool places more emphasis on the "greening by IT" dimension: using digital manufacturing technologies to improve environmental and social performance.

The tool directly links these technologies to relevant ESG dimensions, encouraging users to think critically about how digital investments can drive sustainability outcomes. While the tool does touch on the "greening of IT" by acknowledging trade-offs such as the sustainability footprint of digital solutions themselves, it does not offer concrete guidance on how to minimize those negative impacts. As a result, the "greening of IT" side is addressed more as context than as an actionable component.

One particularly important aspect of the "greening of IT" is the rebound effect. While digital solutions often enable greater energy and material efficiency, these improvements are typically framed in relative rather than absolute terms. Efficiency gains can reduce resource use per unit produced, but if that increased efficiency enables higher production volumes, total resource consumption and emissions can actually rise (Berner et al., 2022). In such cases, the initial sustainability benefit can be partly or entirely offset.

The current version of the tool does not explicitly capture this rebound risk. It highlights how digital technologies can support sustainability targets, but it does so qualitatively and does not calculate net absolute outcomes. This means that potential offsetting effects, where efficiency gains are undermined by increased output, remain outside the scope. Recognizing this limitation is important for users and for future research aiming to strengthen the tool's systemic perspective.

7.2.2. Methodological boundaries and their implications

In addition to the deliberate scoping choices, the methodological approach itself introduces limitations that affect how the research findings could be interpreted and where future work could extend them.

Literature review limitations

The structured literature reviews, although extensive (covering more than 800 and 600 sources respectively) also highlight some important constraints. The interdisciplinary nature of Twin Transition research made systematic coverage inherently challenging.

Relevant work is scattered across multiple fields, including industrial engineering, sustainability studies, information systems, and organizational science. As a result, important insights may be embedded in literature that uses different language or conceptual frameworks. Even with careful search strategies, this disciplinary fragmentation creates a risk that key contributions were missed.

Additionally, the focus on English-language publications, though practical, may also have excluded important local perspectives. For a study grounded in Dutch high-tech manufacturing, this language boundary is especially relevant, as local policy frameworks, sector dynamics, and business practices are often better documented in Dutch-language sources.

These limitations shape the theoretical base and practical framing of the research. The challenges identified in Phase 1 and the requirements formulated in Phase 2 inevitably reflect the scope of literature covered. As such, they may offer an incomplete or partial picture of the full range of issues and opportunities related to the Twin Transition.

Interview methodology and stakeholder representation

The use of semi-structured interviews in this research was well suited to the study's exploratory aims but introduces certain limitations that affect the depth and diversity of insights gathered. The total of 19 interviews conducted across the different research phases provided valuable initial input, but no theoretical saturation was achieved. This is a notable constraint, given the range of perspectives needed to fully understand complex, multi-stakeholder issues like the Twin Transition.

The distribution of interviews across stakeholder groups further shaped the breadth of input. In some categories, only one or two representatives participated, which limited the diversity of views captured within those groups. For instance, the small number of operational managers interviewed means that some practical, shop-floor level challenges may not have been fully surfaced. This creates a risk that the decision-support tool is weighted more towards strategic or advisory perspectives, potentially at the expense of insights on day-to-day implementation realities.

The choice of a semi-structured format offered flexibility and allowed important themes to emerge organically. However, this same flexibility introduced some variation in how questions were posed and answered, which may affect the consistency and comparability of insights across participants. Additionally, interview guides were designed based on the initial literature findings, which, while providing structure, may have inadvertently directed participants towards certain predefined themes. This can constrain the discovery of unexpected issues or requirements that could have broadened the tool's relevance.

Timing is another factor to consider. All interviews were carried out within a limited time window. This means that the stakeholder insights reflect a specific moment in an evolving regulatory and technological landscape. As the Twin Transition continues to develop, stakeholder perspectives, and the challenges they prioritize, may shift. The research therefore captures an important snapshot, but does not address how these dynamics might change over time.

Tool development and evaluation

The tool development process in this research followed a single design-build-test cycle for the full design, which was a practical choice given the time and resource constraints of a Master's thesis but differs from the more iterative approach generally recommended in Design Science Research (Johannesson and Perjons, 2014, p.138). This is a significant methodological boundary with implications for the tool's functionality, usability, and overall robustness.

Without multiple rounds of refinement, some usability issues or design assumptions may not have been fully tested or resolved. In practice, many complexities in how users interact with decision-support tools only become clear through repeated cycles of use, feedback, and redesign (Johannesson and Perjons, 2014, p.137-138). The single-cycle approach therefore means that functional gaps, interface challenges, or unforeseen user needs may persist in the current version of the tool.

The format of the demonstration sessions also shaped the evaluation process. The guided walkthrough approach allowed for targeted and structured feedback collection, but it may have introduced facilitator bias. Participants were not given the chance to explore the tool fully on their own terms, which can limit the ability to identify issues that arise under normal, unsupervised use.

Finally, the composition of the evaluation participants represents one of the more important limitations in assessing the tool's real-world applicability. Three of the four demonstration sessions were conducted with consultants rather than direct users within manufacturing firms. While consultants brought valuable insights based on their client-facing experience, their feedback may not fully reflect the day-to-day realities, practical constraints, and decision-making contexts that actual end-users in manufacturing settings would face.

This creates a risk that the tool's performance under real operational conditions remains only partially understood. Consultants may naturally view and use the tool differently than internal managers or operational staff, perhaps focusing more on structured recommendations for clients and less on the practical, iterative decision-making that characterizes internal industrial planning. As a result, some usability challenges, practical barriers, or context-specific needs relevant for in-house teams may not have surfaced during the evaluation.

7.2.3. Reflection on researcher's positionality

In qualitative research, the interviewer plays a central role in data collection and interpretation, inherently shaping the findings (Johannesson and Perjons, 2014, p.57-58). Because researcher positionality cannot be fully neutralized, transparency regarding the researcher's background is important to contextualize the results of this thesis.

All interviews were conducted by Marie-Anne de Gier, an MSc student in Industrial Ecology and Management of Technology, with a BSc in Applied Physics all at TU Delft. Although trained in research methods, she had no prior experience conducting scientific interviews or working in the Dutch high-tech manufacturing sector.

This background likely influenced both the direction of the interviews and the responses given. For instance, her expertise in sustainability often led conversations to emphasize that dimension of the Twin Transition over digital transformation. In one case, a participant discussing digital strategy spontaneously acknowledged the lack of integration with sustainability, an insight that may not have surfaced without the researcher's sustainability background. Similar dynamics may have shaped other responses, especially those related to ESG topics.

The researcher's position as a graduation intern at Accenture Industry X also shaped the study in several ways. Positively, it provided privileged access to relevant experts across disciplines, ranging from strategy to engineering, and the internship facilitated easier contact through the internship supervisor. This access significantly accelerated the research process. For example, internal resources such as Accenture's compendium of digital manufacturing technologies and sustainability frameworks (including the MSCI ESG Industry Materiality Map) gave the researcher a structured and efficient starting point for investigation. Although similar sources might have been found through academic or public channels, access to curated internal material helped streamline the work.

The internship also meant the researcher benefited from additional supervision by a company expert with sector-specific knowledge. This guidance helped ground the research in real-world industry dynamics, ensuring greater relevance to Dutch high-tech manufacturing practice.

However, this setting also introduced potential biases. Many interviewees were Accenture consultants, albeit from different departments and backgrounds, which may have led to an overemphasis on themes aligned with Accenture's organizational lens. For instance, the frequent focus on data availability and integration challenges in both the challenges identification of Phase 1 and the requirement definition of Phase 2 by interviewees, might reflect the firm's data-driven culture and emphasis on delivering "360-degree value." Similarly, the manufacturing company interviewees consulted during the demonstration phase were Accenture clients, potentially increasing alignment with the firm's perspectives.

Additionally, access to proprietary Accenture material may have subtly shaped the research direction. While these resources accelerated the process, they may have influenced the balance between

academic and grey literature sources, potentially narrowing the scope of perspectives included. In summary, the researcher’s academic and professional positioning brought both advantages and limitations. While it enabled access and practical grounding, it also introduced potential framing effects that could be considered when interpreting the findings.

7.3. Reflection on a tool’s capacity to enable Twin Transition navigation

This research adopts Design Science Research (DSR) as its methodological foundation to develop a practical decision-support tool for Dutch high-tech manufacturers navigating the Twin Transition. This choice has shaped both the research process and its outcomes. To clarify this influence, this section discusses how DSR’s strengths and limitations have affected how the Twin Transition is framed, studied, and addressed in this thesis.

DSR’s main strength lies in its focus on creating practical artifacts (Johannesson and Perjons, 2014, p. 7), which aligns well with the applied needs of the Dutch high-tech manufacturing industry. By moving step-by-step, from identifying the problem and defining requirements to designing and testing a solution, DSR supports the development of tools that practitioners can use directly. This helped ensure that the tool developed responds to real industry needs and does not remain a purely academic exercise. As shown in the evaluation, the tool acts as a “conversation starter” and bridges departmental gaps, illustrating the practical benefits of DSR’s solution-oriented approach (Johannesson and Perjons, 2014, p.3).

However, this strong focus on building an artifact also shapes how the Twin Transition is framed and understood in this research. Because the research centers on delivering a usable tool, it frames the Twin Transition as a challenge that can be addressed through structured, rational methods. This naturally favors solutions that can be designed, measured, and implemented, such as clear frameworks, dashboards, and quantifiable metrics. As a result, the research assumes from the outset that the navigation challenges Dutch high-tech firms face can indeed be tackled through a decision-support tool.

This central assumption, that a decision-support tool can enable Twin Transition navigation, rests on two more basic assumptions. First, that the Twin Transition is a structured challenge that can be solved with a structured solution. Second, that decision-makers are rational actors who want to connect digital and sustainable transformation in the first place. This hierarchy of assumptions is shown in Figure 7.1.

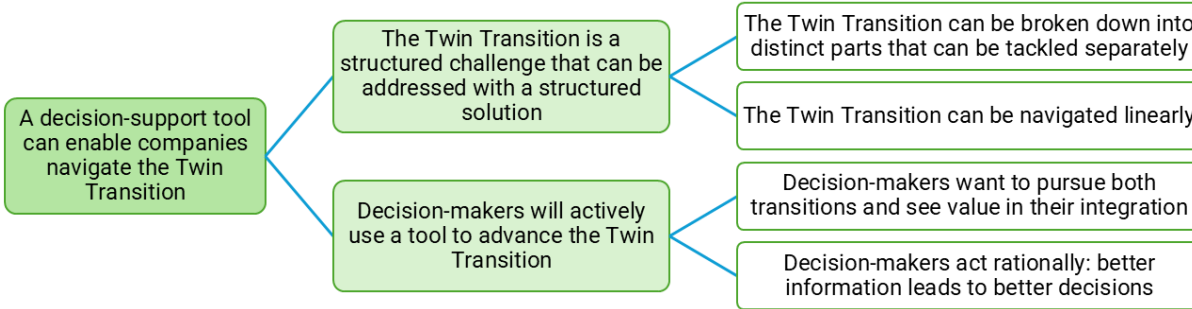


Figure 7.1: Overview of the underlying assumptions that guided the design and development of the Twin Transition decision-support tool.

7.3.1. Reflection on the Twin Transition nature

One of DSR’s core strengths lies in its ability to decompose complex problems into manageable components that can be addressed through targeted interventions (Johannesson and Perjons, 2014, p.93-95). This research demonstrates this approach effectively: the broad challenge of implementing the Twin Transition was broken down into specific, actionable sub-problems, of which a selection was addressed through corresponding tool features. The survey component addresses information gaps, the maturity model provides benchmarking capabilities, and the recommendation system offers tailored guidance based on company-specific contexts.

This decomposition strategy has enabled the development of a coherent, usable solution. However,

it also reflects a particular way of understanding complexity that may not fully capture the systemic nature of the Twin Transition. Challenges like regulatory changes, market dynamics, and cultural factors are deeply intertwined and often extend beyond what any single organization can control.

The Twin Transition represents what might be characterized as a "wicked problem", one that is difficult to define, has no clear stopping point, and cannot be solved through traditional analytical approaches (Johannesson and Perjons, 2014, p. 2). Such problems often require approaches that embrace emergence, experimentation, and learning rather than predetermined solutions (Bender-Salazar, 2023). While DSR incorporates iterative elements through its demonstration and evaluation phases, its fundamental logic remains oriented toward developing a stable artifact.

DSR & the Stacey Matrix: addressing complexity through decomposition

Because the DSR leads to a targeted intervention, the Stacey Matrix was employed to select Twin Transition challenges where a decision-support tool can add the most value: in situations with clear objectives but uncertain technological pathways (see Chapter 3). By selecting challenges that could be addressed through structured approaches, the study has created a manageable scope for tool development. However, it also left out the more systemic and unpredictable elements of the Twin Transition, those with emergent properties and non-linear relationships.

This raises a critical question: are the four selected challenges really the most important barriers to Twin Transition implementation? While these challenges are clearly significant, being "suitable for decision-support" might not mean they are the most critical for success. This points to a potential gap between what structured tools can address and what Dutch high-tech manufacturing companies most urgently need to tackle. For example, excluding employee resistance (Challenge 7) overlooks the human side of technology adoption, yet research on technology acceptance shows human resistance is often a main reason why technical solutions fail (Molino et al., 2020).

Focusing only on challenges that fit structured tools risks optimizing solutions for a narrow part of the problem while leaving larger systemic barriers unaddressed (Johannesson and Perjons, 2014, p. 3). Still, this selective focus is not without merit. In engineering and project management, modularity and black-boxing help manage complexity by breaking systems into smaller, manageable parts (Oehmen et al., 2015). Similarly, this research's targeted scope can support companies tackle clear decision areas, build capabilities step by step, and gradually work toward more complex issues within the Twin Transition. This staged approach can reduce decision paralysis and make transformation more actionable, even if it does not solve every underlying challenge at once.

The key question is whether this enabling effect is enough, or whether a selective tool leaves the core systemic challenge only partially solved. The Stacey Matrix shows that many Twin Transition issues are complex or chaotic. For these, adaptive and participatory methods may be more appropriate than structured, rational tools. This reveals deeper questions about whether structured decision-support is appropriate for Twin Transition implementation at all.

Nevertheless, the chosen selective approach makes meaningful contributions within its boundaries. The final decision-support tool does not offer comprehensive Twin Transition support, but builds a foundation for better decision-making in defined areas. The research also shows the value of systematic challenge identification and categorization, even if the final selection is imperfect. The Stacey Matrix helped reveal the nature of Twin Transition challenges and highlighted where structured tools may fall short. These insights are valuable for both Twin Transition research and decision-support tool development. Additionally, this focused approach may be more practical than aiming for a comprehensive solution. Companies often struggle to allocate resources and prioritize in complex change initiatives (Oehmen et al., 2015). A targeted tool can help them make progress in manageable steps rather than becoming overwhelmed by the full scope of the Twin Transition.

DSR, MoSCoW, and sub-dimension selection: managing complexity through prioritization

The methodological choices around requirement prioritization and the selection of sustainability dimensions highlight a similar tension in DSR's approach to complex problems: balancing practical, actionable solutions with a complete understanding of the underlying challenges. Using the MoSCoW prioritization framework, combined with EEIOA and MSCI materiality mapping, is a structured way to handle this complexity through clear prioritization. However, this reduction method has important consequences for how the Twin Transition is framed and addressed.

Choosing MoSCoW for requirement prioritization reflects DSR's emphasis on stakeholder input. This approach has clear benefits: it helps distinguish essential from optional features, supports efficient use of limited resources, and grounds the tool in practitioner needs rather than only academic ideas (Agile Business Consortium, 2014). Its four categories (Must-have, could-have, Could-have, and Won't-have) create a practical hierarchy, which is especially useful in time-constrained projects like a Master's thesis. The interviews in the Demonstration & Evaluation phase also show this worked well in practice: the clear stakeholder feedback justifies the tool's main features and suggests the MoSCoW method successfully highlighted user priorities.

However, MoSCoW also has clear conceptual limits. It assumes that requirements can be ranked separately, treating the tool as a set of individual features rather than an integrated system (Stapleton, Jennifer, 1997). This can hide important connections between elements. For example, marking "concrete actions" and "skills needed" as "Could-have" implies these are nice-to-have extras, not essential parts of strategic guidance. Yet research shows that success in organizational change relies heavily on clear action plans and capability building (Molino et al., 2020). By splitting these off as optional, the prioritization may weaken the tool's ability to drive real change.

The MoSCoW method also assumes that stakeholders know enough to rank requirements accurately based on their current experience (Stapleton, Jennifer, 1997). This is problematic for emerging challenges like the Twin Transition, where old practices may not fit new demands. The focus on quantification and structured analysis reflects current organizational strengths, but may not match what true transformation requires. This raises a key question: does stakeholder-driven prioritization strengthen today's practices, or does it risk locking the tool into current ways of working when deeper change is needed?

The use of EEIOA data and the MSCI Materiality Map aims to define sustainability dimensions with solid evidence rather than subjective judgment. EEIOA offers quantitative data on actual environmental impacts in Dutch high-tech manufacturing, identifying material impacts through measurable flows. The MSCI framework systematically identifies ESG factors that are financially material, using broad industry analysis and stakeholder input. Together, they build a solid empirical basis for deciding which sustainability aspects the tool could cover, ensuring relevance both environmentally, socially and economically. This approach has clear strengths. It reduces subjective bias by using quantitative data (Johannesson and Perjons, 2014, p. 55). The production-based EEIOA method ensures the data reflect real impacts in Dutch manufacturing rather than generic sustainability metrics.

However, this approach also introduces constraints that shape how sustainability is defined. EEIOA is limited by what data are available. Some impacts must still be reviewed qualitatively. More fundamentally, EEIOA measures what can be counted through monetized flows, which risks sidelining aspects of sustainability that are hard to quantify but important in the long run. The MSCI framework has a similar financial foundation: it focuses on ESG factors that affect company value and investor risk. This fits well with the research's identification of investment uncertainty as a key Twin Transition challenge, but it also means that environmental and social issues are valued mainly for their financial impact. This can underplay sustainability challenges that are important, but do not translate easily into near-term financial risk (Sørensen and Pfeifer, 2011).

This financial lens can be especially limiting for long-term, systemic challenges like climate change, biodiversity loss, or social inequality, which often play out over decades which is far beyond typical investment horizons (Sørensen and Pfeifer, 2011). By focusing on what is financially material now, the tool may end up emphasizing risk management over real systemic change.

Finally, both methods break sustainability impacts into separate parts that can be assessed independently for their importance to the Dutch high-tech manufacturing sector. This helps manage complexity, in line with DSR's artifact-focused approach. But it misrepresents the true, interconnected nature of sustainability issues. Impacts often interact in complex ways (Jones et al., 2010). For example, water consumption may interact with energy systems through cooling requirements, with material systems through manufacturing processes, and with social systems through community resource access.

Systems thinking shows that sustainability challenges emerge from these connections and feedback loops, not from isolated elements (Jones et al., 2010). While the research acknowledges obvious linkages such as energy consumption and greenhouse gas emissions, it explicitly excludes less obvious but potentially more important system-level interactions. These interactions often produce non-linear

effects where small changes in one dimension create disproportionate impacts in others. By treating impacts mostly as separate pieces, the tool risks missing key interactions that shape real-world sustainability outcomes.

Maturity model: handling complexity through linearization

In line with the simplification of the Twin Transition's interconnected sustainability dimensions, the decision-support tool uses a five-level maturity model (descriptive, diagnostic, predictive, prescriptive, and adaptive) to break down transformation into a clear, staged transition. This framework assumes that progress follows a cumulative, linear logic: capabilities build in a set order, companies can be benchmarked against standard progression tracks, and moving up the levels consistently leads to better outcomes (De Bruin et al., 2005). While this structured approach helps manage complexity and provides clear guidance, it also brings important limitations that shape how the Twin Transition is framed and tackled.

The maturity model's linear structure offers clear practical benefits that fit well with DSR's artifact-oriented approach. It gives organizations a roadmap, which helps reduce the sense of being overwhelmed when dealing with the Twin Transition's many demands. By dividing transformation into clear, measurable stages, the model makes broad goals like "digital-sustainability integration" concrete and actionable. The stepwise design also makes it easier to benchmark progress against peers and track improvements over time—addressing the sector's need for clearer pathways from intention to action (Barry et al., 2023).

The model's staged logic also reflects real-world technological dependencies. For example, companies often need basic data gathering systems (descriptive level) before they can move to predictive analytics (predictive level) (Barry et al., 2023). This cumulative order captures real constraints in learning and technology adoption, grounding the progression in practical realities rather than abstract theory.

However, this linear framing ultimately simplifies the reality of how digital and sustainability transitions unfold within organizations. In practice, change rarely follows a neat, stepwise sequence. Companies may bypass stages altogether by adopting advanced technologies before establishing foundational capabilities, develop deep expertise in specific areas while remaining underdeveloped in others, or even regress due to shifting strategies, leadership changes, or external disruptions (Barry et al., 2023). This difference is visualized in Figure 7.2.

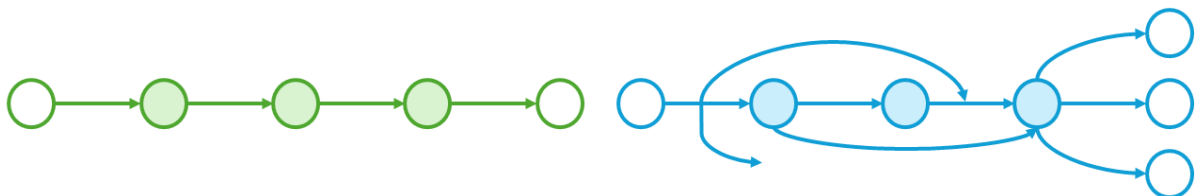


Figure 7.2: Visualization of how the linear maturity model looks (in green), vs how the transition process actually might be in reality (in blue).

More critically, the model's underlying assumption that "higher" levels necessarily equate to "better" outcomes embeds a particular vision of technological progress that may not align with every organization's context or sustainability objectives (Mullaly, 2014). For example, positioning adaptive, AI-driven systems as the ultimate goal of maturity suggests that ever-greater technological sophistication is always desirable. Yet, for some companies, more straightforward solutions may deliver greater sustainability benefits at lower cost and with fewer risks. By prescribing a single, idealized progression path, the model risks steering companies toward investments that fit its internal logic rather than what is most appropriate for their unique circumstances (Mullaly, 2014). Organizations prioritizing degrowth strategies, circular economy principles, or broader social sustainability aims may find that this technology-centric Twin Transition trajectory conflicts with their overarching goals. While the tool provides clear guidance for its intended audience, it does not fully accommodate the diverse pathways that sustainability may require in practice.

Moreover, by institutionalizing a fixed sequence of stages, the maturity model privileges certain types of change (incremental, linear, and technologically driven) over approaches that may be more radical, emergent, or socially oriented (Mullaly, 2014). This framing not only shapes how practitioners

navigate the tool but also subtly influences how future research might conceptualize what effective support for the Twin Transition could entail.

7.3.2. Reflection on the decision-maker nature

The effectiveness of any decision-support tool fundamentally depends on the assumptions made about its intended users. This research centers on strategic managers and consultants as the primary decision-makers who can drive Twin Transition implementation. However, this focus reflects deeper assumptions about who has agency in organizational transformation, what motivates their decision-making, and how they conceptualize the relationship between digital and sustainability initiatives.

Underlying assumptions about the Twin Transition's desirability

This study implicitly assumes that the Twin Transition is an inherently desirable pathway for Dutch high-tech manufacturers, treating practical challenges as hurdles to be overcome rather than potential indicators that the concept itself may not fully align with firms' strategic priorities. This foundational assumption shapes the tool's entire design and constrains its relevance for organizations whose strategies may not fit this vision.

At its core, this assumption rests on three interlinked beliefs: that digital transformation is both inevitable and beneficial, that sustainability transformation is an unavoidable organizational imperative, and that integrating the two creates additional value. Each of these beliefs carries significant implications for how the tool frames organizational choice and strategic agency.

Digital transformation as an inevitable choice Throughout this research, digital transformation is positioned as the default strategic path for Dutch high-tech manufacturers. The interview protocol, maturity model, and the decision-support tool itself all presuppose that companies intend to advance, at varying paces, along a digital transformation pathway. Alternative strategies, such as deliberate non-adoption, purposeful slowdown, or "digital minimalism", receive no attention.

Because the tool starts its assessment with a company's self-defined digital ambitions, it does not question whether these ambitions are necessary or appropriate to begin with. While the survey technically allows a company to indicate that its desired maturity matches its current state, doing so effectively disables the tool's capacity to recommend digital measures and, by design, removes its pathway to improved sustainability performance. In this sense, the tool equates greener operations with greater digital maturity.

Recent data challenge this assumption. According to Statistics Netherlands (CBS) (2025a), Dutch industrial firms plan to direct about 25% of near-term capital expenditures toward sustainability measures, but only around 3% toward digital transformation. This strong gap suggests the connection assumed by the Twin Transition may not reflect how many firms actually allocate resources.

Sustainable transformation as a necessary imperative Alongside the digital assumption, this research also presumes that sustainability transformation is an inherent goal for companies. Yet, findings from the interviews (particularly in Phase 1) indicate that Dutch high-tech manufacturers do not typically pursue sustainability for its own sake. Instead, compliance with regulation is the main driver, specifically in response to frameworks like the European CSRD.

However, a compliance-driven approach creates a fundamentally different context than one grounded in intrinsic sustainability ambition. When firms view sustainability through a compliance lens, they are more likely to aim for minimal legal adherence rather than substantial transformation (van Prooijen et al., 2021). This has important implications for what decision-support tools can realistically achieve, and for how they are designed.

This is especially important as recent regulatory changes directly undermine this compliance-based driver for sustainability performance improvement. Major revisions to the CSRD in early 2025 drastically raised the employee threshold for applicability, resulting in an estimated 75–82% reduction in the number of companies required to do CSRD reporting (Mennens and Koolstra, 2025). Reporting deadlines for affected companies have also been pushed back by two years, and proposals from June 2025 would raise thresholds further, make climate transition plans voluntary, and restrict stricter national measures (Garden, 2025).

These developments significantly weaken the regulatory push that underpins the tool's relevance. If mandatory compliance pressure drops, the main motivator for sustainability transformation identified

in this research may no longer hold for much of the sector. This calls into question whether sustainability transformation remains a practical priority, and whether tools built to facilitate it retain their strategic usefulness.

The shifting policy landscape also highlights the inherent fragility of compliance-led transformation. If regulatory obligations are relaxed or withdrawn, tools built primarily to support regulatory alignment lose much of their value (van Prooijen et al., 2021). This suggests that effective decision-support must also create clear business value beyond compliance, even if intrinsic sustainability commitment remains limited in the sector.

Twin Transition as a policy-driven construct Even if one assumes that companies want both digital and sustainability transformations, whether they are motivated to actively integrate these into a unified Twin Transition is a separate question. This research treats the integration as a logical next step, but this largely mirrors EU policy ambitions rather than company-led priorities.

The Twin Transition concept emerged as part of the European Union's Green Deal, which framed digitalization as a critical enabler of environmental progress (Muench et al., 2022). The COVID-19 pandemic revealed the vulnerabilities of global supply chains and accelerated discourse around strategic autonomy, intertwining digital transformation, sustainability, and economic security under one policy banner (Belu, 2024). Recovery funds were channelled toward this Twin Transition narrative to improve European resilience and reduce dependency on external suppliers, particularly for high-demand sectors like semiconductors.

However, this policy logic does not necessarily align with how companies themselves frame their strategies. In this study, none of the Dutch high-tech manufacturers examined explicitly refer to the Twin Transition in any public-facing materials. More broadly, references to the Twin Transition are highly scarce in industry communications. This raises a critical point: is the Twin Transition truly a pull from companies, or primarily a push from policymakers? The absence of this language in company strategies suggests that while firms may engage in both digital and sustainability activities, they do not necessarily see these as a single, integrated transformation, or at least not yet. This misalignment has practical implications: decision-support tools designed around the assumption of integration may face adoption challenges or be used in ways that diverge from their intended purpose.

Moreover, even the EU's own framing of the Twin Transition is shifting. Research by Belu (2024) shows how "strategic autonomy" and "economic security" have gradually moved the discourse into the defense domain. What began as an environmental-digital integration strategy has increasingly incorporated military and security objectives. By 2024, with a new European Parliament and Commission, momentum behind the Green Deal has weakened, replaced in part by a stronger focus on defense spending and security. This timeline is visualized in Figure 7.3. This evolution reveals the Twin Transition as a fluid, policy-driven construct rather than a stable domain. For tools built on this concept, such instability raises questions about long-term relevance and coherence. If the policy focus shifts yet again, the assumptions embedded in the tool may quickly become misaligned with both the political context and companies' actual strategic needs.



Figure 7.3: Overview of the changing Twin Transition narrative focus over time. Adapted from Belu (2024)

The rational actor assumption and its implications

Then assuming that the decision-makers want to operate in the Twin Transition context and connect the two transitions, the logic behind DSR and the developed decision-support tool relies on the idea that decision-making improves when decision-makers have better tools and information. This follows the rational actor model: if decision-makers have clear data and structured frameworks, they will act

optimally (Johannesson and Perjons, 2014, p. 122). The decision-support tool applies this logic by offering structured comparisons, quantified trade-offs, and evidence-based recommendations.

Evaluation results confirmed the tool's practical value for participants. Still, this approach reflects a specific view of organizational change: one that sees information gaps and coordination problems as the main barriers. However, many of the identified Twin Transition challenges that this sector experiences as outlined in Phase 1, run deeper. For example, Challenge 10 (regulatory navigation) was excluded because shifting policies made it "chaotic" and not suitable for structured support. Yet, regulatory uncertainty heavily affects strategic planning, which is precisely the area where support is needed most. This shows a contradiction: the same unpredictability that makes this challenge hard to address with a tool also makes it critical to tackle.

Additionally, DSR's rational focus assumes that better knowledge leads directly to better action. However, extensive research in organizational studies and sustainability transitions suggests that this relationship is often more complex, mediated by power dynamics, institutional pressures, and cultural factors that resist purely rational intervention (Stergiou et al., 2023). A decision-support tool alone can therefore not fully overcome these factors.

7.4. Recommendations for future research

7.4.1. Improving generalizability

Sector-specific adaptation and validation

The sector-specific findings for Dutch high-tech manufacturing demonstrate both the value and the necessity of tailoring Twin Transition frameworks to distinct industrial contexts. Future research could build on this by systematically extending the approach to other manufacturing sectors, especially those with very different environmental profiles or digital maturity baselines. Priority areas might include heavy industries such as steel and cement, where emissions profiles and operational realities differ substantially (Gross, 2021). As well as continuous process industries like chemicals and pharmaceuticals, where digitalization challenges differ from those found in discrete manufacturing (Proctor et al., 2010).

Each sectoral extension could adopt a similar methodological structure: conducting sector-specific EEIOA analyses to map material impacts, linking relevant digital technologies to sector processes, and validating the resulting frameworks through stakeholder engagement within that sector. This would gradually build a library of sector-specific Twin Transition tools, while testing the transferability of the underlying research design. Comparative insights across these frameworks could then reveal broader patterns about how digital transformation and sustainability interact under different industrial conditions, contributing to more generalizable theory as well as practice.

Cross-national comparative studies

The geographical focus on the Netherlands enabled this study's depth and practical grounding, but it also means that the national context inevitably shapes the findings. Future research could extend this by conducting comparative studies across European countries with different industrial structures, policy landscapes, and sustainability governance traditions. Contrasting contexts could show how national innovation systems and policy frameworks shape the Twin Transition in practice.

Such comparative studies could look not only at policy differences, but also at how business cultures, stakeholder expectations, and technological capabilities vary. Comparing, for instance, the Netherlands' collaborative governance style with more centralized or hierarchical systems could highlight how institutional factors influence the feasibility and impact of integrated digital-sustainability approaches. This would be especially relevant given that EU-wide frameworks like the CSRD must be implemented across these diverse national contexts.

Small and medium-sized enterprises (SMEs)

The current study's focus on large enterprises inevitably leaves a gap when it comes to small and medium-sized firms, even though these businesses make up the majority of manufacturing companies and face unique challenges. While working with large firms brought depth and practical validation, it underscores the need for dedicated research to understand how SMEs navigate the Twin Transition under very different conditions.

Future studies could develop SME-specific frameworks that recognize the distinct constraints and capabilities smaller firms bring. SMEs often operate with leaner structures, tighter budgets, and less dedicated technical expertise than large firms (Nunes et al., 2012). Rather than trying to retrofit large-enterprise models, future work could investigate how SMEs manage Twin Transition pressures in ways that reflect their own strengths (agility, closer decision chains, and the ability to implement rapid, incremental changes).

This could reveal alternative pathways that differ from the linear maturity models suited to large organizations. It would also be valuable to explore how SMEs can adopt advanced digital tools without significant upfront investment. Shared infrastructure, cloud-based solutions, and stepwise rollouts could all help smaller firms benefit from the Twin Transition while managing risk (High Tech NL, 2023). Collaborative models (such as consortia or sector-specific service platforms) may further enable SMEs to pool resources and expertise, supporting inclusive industrial digital transformation and sustainability.

7.4.2. Addressing systemic and rebound effects through an Industrial Ecology perspective

Comprehensive lifecycle and system boundary analysis

The clear process-level focus of this research made it possible to establish direct links between digital tools and sustainability outcomes. However, this boundary also leaves critical system-level dynamics out of scope. To strengthen future Twin Transition research, system boundaries could expand to cover entire product lifecycles, upstream supply chains, and end-of-life phases (Scope 3) (Font Vivanco and van der Voet, 2014).

This would require methods that can trace local process optimizations through global value chains, which is important in high-tech sectors with complex supply networks. Advanced Industrial Ecology approaches, such as dynamic lifecycle assessments, could quantify whether process-level efficiency gains translate into absolute system benefits (Font Vivanco and van der Voet, 2014). For example, if digital tools reduce material waste in production but enable greater production output, the net impact depends on the scale of these opposing effects. This calls for dynamic modeling that can map feedback loops between efficiency improvements and production growth.

Rebound effect quantification and mitigation

This study identifies the rebound effect as a critical blind spot in how digital technologies are currently assessed. Future work could develop systematic methods to quantify and mitigate rebound effects in digital manufacturing contexts. This means going beyond relative efficiency metrics to track absolute resource use and emissions.

One promising avenue could be the development of hybrid models that combine engineering-based process data with economic models of production scaling and market behavior. Such models would help clarify how efficiency gains affect costs, pricing, and ultimately demand, providing a more realistic estimate of total sustainability impacts. By capturing both direct and indirect effects, this approach could help companies and policymakers identify where additional safeguards or incentives are needed to ensure that efficiency improvements do not unintentionally drive up total resource use.

Socio-technical system dynamics

Finally, this research reaffirms that digital technologies could not be understood as purely technical interventions but as elements embedded within broader socio-technical systems. Future studies could develop frameworks that better capture how technological capabilities, organizational structures, and social practices interact and co-evolve in Twin Transition contexts.

This could include examining how different organizational forms, for example, hierarchical versus networked or centralized versus decentralized structures, shape whether digital investments deliver real sustainability gains. It could also explore how workforce skills, managerial practices, and corporate cultures enable or constrain the intended benefits of digital tools. Such research would contribute to a deeper, more practical understanding of when and how digital transformation genuinely supports systemic sustainability transitions, rather than just optimizing the status quo.

7.4.3. Reconceptualizing the Twin Transition

Bottom-up Twin Transition emergence

This research highlights a gap between high-level, policy-driven notions of the Twin Transition and the practical realities of how companies actually set their strategic priorities. Future research could explore how integration between digital transformation and sustainability emerges organically within firms, often shaped less by formal frameworks and more by operational needs and business pressures on the ground.

Such studies could examine how companies manage the simultaneous demands of digital and sustainability goals in day-to-day operations, revealing integration patterns that develop out of necessity rather than top-down strategic intent. Insights from this bottom-up perspective could identify alternative models of Twin Transition that are better aligned with real business logic, offering practical lessons for policymakers seeking to design supportive, rather than prescriptive, policy frameworks.

Post-rational decision-making

The design of decision-support tools often assumes rational decision-making: that clear information, structured frameworks, and systematic guidance will directly translate into better choices. However, real-world organizational decisions about digital and sustainability investments often play out under conditions of uncertainty, competing objectives, and internal politics.

Future research could therefore investigate how companies actually make such decisions when rationality is bounded by incomplete information, time constraints, and social dynamics. This could involve developing new decision-support methods that explicitly account for behavioral biases, emergent strategies, and political negotiation inside organizations.

7.4.4. Addressing the changing policy landscape

Regulatory impact assessment and adaptation

The significant changes to CSRD requirements during 2025 illustrate the evolving and sometimes unpredictable nature of the policy environment that underpins Twin Transition efforts. This policy volatility raises practical questions about how companies can plan and invest in long-term digital and sustainability capabilities with confidence. Future research could examine how shifting regulations affect the business case for Twin Transition investments. This could involve developing scenario-based methods that help firms test strategies under different future policy conditions, supporting better preparedness and flexibility in the face of regulatory change. Such work could also inform policymakers by showing how unstable rules can shape, delay, or even deter private-sector investment.

Beyond compliance-driven sustainability

The findings show that regulatory compliance, particularly with CSRD requirements, remains the main driver of sustainability action for many Dutch high-tech manufacturers. While this regulatory push is important, compliance alone may not deliver the deeper, systemic transformation needed to tackle sustainability challenges at their roots.

Future research could examine how companies can be encouraged to move beyond minimum compliance, embedding sustainability more deeply into their core strategies and value creation models. This could include studying how new business models, stronger stakeholder relationships, or values-based leadership practices foster genuine sustainability motivation from within. Such work could also explore how integrated digital-sustainability approaches might unlock new business opportunities, strengthening the Twin Transition business case not just as a regulatory necessity but as a driver of long-term competitiveness and innovation.

7.4.5. Methodological advancement for the tool

Multi-cycle Design Science Research

The research relied on a single design-build-test cycle, which was appropriate for the scope of a Master's thesis but limits how far the tool could be refined in practice. Future research could adopt multi-cycle Design Science Research (DSR) approaches that allow the tool to be tested, improved, and re-tested through real-world use over time.

Such longitudinal DSR would involve deploying the tool in partner organizations, gathering detailed usage data, and using those insights to strengthen both the tool's functionality and its assumptions. This

would be especially valuable for testing whether the maturity model's assumption of linear progression reflects reality, or whether organizations follow more varied and less predictable development pathways.

By tracking how the tool performs as contexts evolve, including changes to internal priorities or external regulations, researchers could build a more resilient and adaptable version that delivers sustained value in dynamic environments.

Validation of Twin Transition effectiveness

This research combines qualitative input with quantitative analysis, but there is room to deepen this mixed-methods integration. Future studies could test the tool's impact more rigorously and at scale. For example, large-scale surveys could map how widespread particular Twin Transition challenges are across different industries, while in-depth longitudinal case studies could trace how these challenges change over time as firms progress in digitalization and sustainability.

A particularly valuable next step would be quasi-experimental research comparing companies that use structured Twin Transition support, such as this tool, with control groups that address digital and sustainability challenges separately. This would help build empirical evidence on whether integrated approaches deliver superior outcomes in practice. Such comparative work would require collaboration with industry partners prepared to take part in extended, structured testing.

7.4.6. Methodological advancement beyond the tool

The use of the Stacey Matrix in this research revealed that many key Twin Transition challenges are inherently complex or even chaotic, contexts in which traditional, structured decision-support tools are likely to fall short. This points to an opportunity for future research to develop more adaptive, participatory methods suited to these conditions.

Such approaches could include co-creation processes that actively involve multiple stakeholders in shaping solutions, or complexity-informed methods that accept uncertainty and emergence as inevitable features rather than problems to eliminate. Future research could also explore how organizations can build internal capacity for continuous learning, experimentation, and course correction, which may prove more effective for addressing issues like cultural change, employee resistance, and strategic alignment than any fixed framework alone.

7.5. Recommendations for Dutch high-tech manufacturers

7.5.1. How to best use the decision-support tool

Use the tool as a cross-functional facilitator

The decision-support tool is designed to function primarily as a facilitation aid rather than a rigid, prescriptive solution. Its main value lies in creating a structured foundation for cross-functional conversations between departments that often operate in isolation, especially IT, sustainability, and operations teams. The survey offers a practical entry point for collaborative workshops where stakeholders can align on shared ESG priorities and digital goals.

Insights from the demonstration sessions confirmed that bringing sustainability managers, digital transformation leads, and operations leaders together around the tool's maturity-gap dashboard can strengthen strategic alignment. The tool's shared visual language and structured outputs help reveal blind spots and encourage mutual understanding across teams. Organizations are therefore encouraged to treat the tool as an enabler for dialogue: a common platform for jointly assessing the current state, clarifying ambitions, and identifying the capabilities needed to bridge the gaps.

Treat missing data as a first-order deliverable

The maturity model results highlighted the central importance of reliable data as the foundation for informed decision-making. Several interviewees noted that even the tool's baseline survey sometimes assumes access to operational or ESG data that companies do not yet systematically collect. This finding shows that data availability could not be treated as a passive constraint, but rather as an active priority in itself.

To address this, manufacturers are advised to develop a short-term "data-for-CSR" roadmap that focuses on the most material and high-impact topics (for example, energy use, fluorinated gas emissions,

and employee safety metrics). Practical first steps could include installing low-cost IIoT sensors or tapping into existing MES or PLC systems to extract underused data. Building a robust data foundation is essential for credible sustainability progress: without it, companies lack the transparency needed to evaluate trade-offs and make confident, evidence-based investment decisions. This recommendation is especially relevant given the CSRD's clear emphasis on measurable, material ESG performance indicators.

Prioritize “no-regret” digital measures for quick wins

To build early momentum and reduce perceived risks, companies could start by focusing on digital measures that offer significant sustainability benefits with relatively low implementation complexity. Practical examples include energy monitoring systems, digital tracking of material use, and predictive maintenance technologies. These “no-regret” solutions provide clear, near-term returns that can help build organizational support and demonstrate the value of digital investments.

Rather than attempting a comprehensive digital transformation all at once, a phased approach is recommended. The decision-support tool's maturity model can help companies plan this progression: starting with straightforward measures that deliver immediate value and then moving towards more advanced solutions, such as AI-driven optimization or closed-loop process controls. This staged pathway helps address two of the key barriers highlighted in this research, high upfront costs and uncertainty about return on investment, by delivering tangible results step by step and creating a foundation for more ambitious improvements over time.

7.5.2. Future developments to prepare for

Changing digital landscape

The digital transformation landscape in manufacturing continues to evolve quickly, with new technologies that could reshape how companies pursue both operational efficiency and sustainability. According to Shikanai et al. (2024)'s hype cycle for advanced manufacturing technologies, several emerging tools could significantly influence the Twin Transition in the coming decade. For Dutch high-tech manufacturers, the challenge is not simply to adopt these technologies, but to build the organizational capabilities and strategic positioning needed to deploy them effectively, all while balancing short-term competitive pressures and regulatory demands. This section outlines three example technologies likely to shape this future, with three different timelines: digital product passports (next 5 years), quantum computing (5-10 years) and the industrial metaverse (more than 10 years). Where these technologies currently are on the hype cycle, is visualized in Figure 7.4.

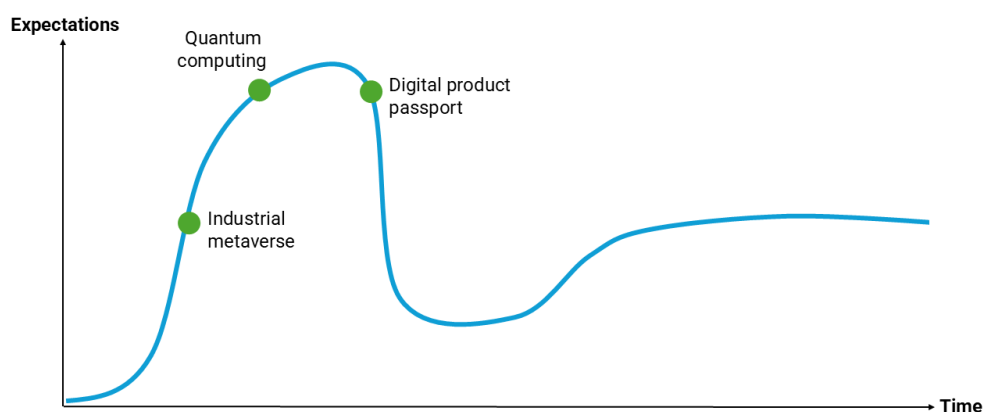


Figure 7.4: Three highlighted technologies and their position on the advanced manufacturing hype cycle, adapted from Shikanai et al. (2024).

One technology to watch is the **Digital Product Passport (DPP)**. Although DPPs are being driven by compliance requirements, they also offer significant opportunities for strategic differentiation and market positioning. DPPs create a practical link between digitalization and sustainability, extending beyond minimum compliance to enable supply chain transparency, customer engagement, and circular economy models (Mittwoch, 2024). Implementing DPPs well requires a strong foundational digital infrastructure, such as IoT sensors, blockchain, and advanced analytics, but directly supports sustainability by providing verified, traceable data on product impacts. For Dutch high-tech manufacturers, DPPs represent a chance to differentiate products based on sustainability credentials while building the digital backbone for more advanced manufacturing capabilities.

However, the value companies gain depends on how they approach implementation. A minimalist compliance mindset may tick regulatory boxes but risks missing wider benefits (Mittwoch, 2024). Firms that treat DPPs as a strategic asset, investing early in real-time data collection, advanced analytics, and customer-facing tools, can turn compliance costs into value-creating capabilities. This demands proactive investment in digital systems and skills before external pressure forces a rushed, reactive action.

Quantum computing is another technology with game-changing potential for manufacturing. Although today's industrial applications remain limited, mostly in simulating advanced physics and chemistry, the technology is progressing towards real-world use cases (Bayerstadler et al., 2021). For high-tech manufacturers, the question is less about immediate investment and more about preparing to harness quantum advantages as they mature. Possible applications include:

- **New materials development:** Quantum computing could enable detailed molecular modeling, allowing firms to design new materials for semiconductors, high-performance alloys, and smart devices (Bayerstadler et al., 2021).
- **Process optimization:** Complex manufacturing processes with many interdependent variables could be optimized simultaneously, reducing waste and energy use.
- **Quality control:** Advanced pattern recognition could enable near-perfect detection of manufacturing defects.

For the Twin Transition, quantum computing could act as a powerful multiplier. On the digital side, it represents a large step in computational capability, while on the sustainability side, it could make new levels of optimization possible that reduce costs and environmental impacts at once.

Yet there are challenges too. Many quantum computers, particularly those using superconducting qubits, operate at temperatures near absolute zero, demanding energy-intensive cryogenic systems (Bayerstadler et al., 2021). As quantum systems scale up, cooling and error correction requirements can drive energy use even higher, creating tension between the promise of sustainability gains and the technology's own footprint.

Given these factors, companies could focus now on building quantum readiness rather than immediate deployment. This means developing in-house computational capabilities, partnering with quantum research institutions, and identifying priority use cases where quantum computing could deliver strategic advantage. Monitoring advances in quantum energy efficiency will also be key to ensuring that net environmental benefits outweigh the technology's energy demands.

Although still early-stage, the **Industrial Metaverse** points to the next frontier for digital manufacturing. Combining digital twins, AR/VR, and AI, the Industrial Metaverse creates a bridge between physical and virtual operations (Bhattacharya et al., 2023). This convergence can enable remote monitoring, virtual maintenance, and collaborative problem-solving, cutting travel-related emissions and increasing operational flexibility. Virtual prototyping and testing reduce the need for physical trial-and-error, saving time and materials. These advances directly support Industry 5.0 ambitions for sustainability, resilience, and human-centric production.

However, realizing the Industrial Metaverse's benefits depends less on technology acquisition and more on organizational readiness. Companies will need to develop digital twin capabilities, pilot AR/VR in specific processes, and build the underlying data infrastructure for integrated virtual-physical workflows (Bhattacharya et al., 2023). Equally important is workforce development: employees must be trained to work effectively with immersive technologies, while change management practices will be critical to align people, processes, and new digital capabilities.

How the high-tech sector landscape will develop

Beyond specific technologies, broader shifts in the global industrial landscape will shape how Dutch high-tech manufacturing can pursue Twin Transition goals in the years ahead.

One major trend is the shift away from stable, globalized supply chains towards more regionalized and resilient models (van Kappen et al., 2023). Geopolitical tensions, supply chain shocks, and the push for strategic autonomy are all driving companies to rethink over-optimized, cost-focused networks. Increasing resilience through supplier diversification, near-shoring, and added redundancy, however, can sometimes clash with sustainability goals if it leads to less efficient logistics or limits access to the most environmentally advanced suppliers.

This reality means companies must develop more sophisticated supply chain strategies that optimize for cost, resilience, and sustainability simultaneously, instead of treating these as separate trade-offs (van Kappen et al., 2023). This could include investing in multi-criteria decision frameworks, building deeper partnerships with suppliers that deliver on both resilience and sustainability performance, and using advanced digital tools to model complex supply chain configurations.

Looking further ahead, van Kappen et al. (2023) project that by 2040, a substantial share of revenue for Dutch high-tech manufacturers will come from emerging value chains. This shift presents both opportunities and resource allocation challenges.

For example, healthcare technologies, driven by demographic shifts, could generate demand for innovations like preventive diagnostics, lab-on-a-chip solutions, and personalized medicine (van Kappen et al., 2023). These align naturally with sustainability goals by improving outcomes and reducing resource waste. Similarly, geopolitical instability is driving growth in defense applications that overlap with civilian technologies, such as secure communications, sensors, and autonomous systems.

To seize these emerging opportunities, companies will need to balance investment in new capabilities with maintaining excellence in their existing operations. This calls for careful decisions about where to deploy limited resources for maximum future value. Companies will need to assess how their core competencies can be extended into adjacent markets, and adapt their business models and value propositions to capture growth in these evolving sectors.

8

Conclusion

This thesis sets out to answer the following research question:

What decision-support tool can be designed to support Dutch high-tech manufacturing companies to simultaneously improve their digital capabilities and sustainability performance in line with the Corporate Sustainability Reporting Directive (CSRD)?

To answer this question, the study followed the Design Science Research (DSR) approach as outlined by Johannesson and Perjons (2014), structured across four phases: problem explication, requirement definition, design & development, and demonstration & evaluation. The main research question was decomposed into five sub-research questions, each of which played an important role in informing the design and validation of the decision-support tool.

Phase 1: Explicating the problem

To begin answering the main research question, it was first necessary to understand which challenges companies face in implementing the Twin Transition. This led to the first sub-research question: **“What are the challenges faced by Dutch high-tech manufacturing companies in implementing the Twin Transition?”**

To explore this, a structured literature review was conducted using the PRISMA method for literature identification, covering over 800 academic sources. This process identified thirteen common challenges associated with implementing digital and sustainability transformations in manufacturing companies. These were then discussed in eight expert interviews with stakeholders involved in Dutch high-tech manufacturing from academia, industry, and umbrella organizations. Based on these insights, the thirteen challenges were refined to ten challenges that fit the specific context of Dutch high-tech manufacturing.

To better understand the nature of these challenges, they were mapped onto the Stacey Matrix, which helps assess whether problems are simple, complicated, complex, or chaotic. This analysis showed that four of the ten challenges were “complicated”, meaning they are difficult, but still manageable through structured approaches. These challenges were selected as the focus for tool development:

1. High implementation costs combined with unclear returns;
2. Limited visibility into the environmental footprint of digital technologies;
3. A lack of sector-specific transition pathways;
4. The absence of a framework for quantifying trade-offs between digital and sustainability goals.

Phase 2: Defining the requirements

With the key challenges identified, the next step involved answering the second sub-research question: **“What functional, structural and contextual requirements must the decision-support tool meet to support the Dutch high-tech manufacturing sector in addressing the identified Twin Transition implementation challenges?”**

Each of the four main challenges was translated into a desired solution. These solutions were then broken down into functional requirements and sub-requirements. Then, to identify fitting structural requirements, a second PRISMA-structured literature review was carried out, this time focusing on academic models that guide organizational transformation. From a pool of 600 papers, relevant structural requirements were identified by examining how other decision-support tools were structured to address comparable functionalities.

Next, the intended user profile for the tool was developed in collaboration with Accenture Industry X. This profile helped shape the contextual requirements, ensuring that the tool would align with real-world users and their working environments.

To prioritize the different requirements, five semi-structured interviews were conducted with individuals who matched the intended user profile. During these sessions, a MoSCoW framework (Must-have, Should-have, Could-have, Won't-have) was used to determine which requirements were most important. Key functional requirements included the ability to apply company-specific weightings and the need for visual representations of trade-offs. Seven structural elements were identified as essential, including clearly defined maturity levels and hierarchies of key performance indicators (KPIs). In addition, two contextual requirements were emphasized: the tool should support dialogue between departments rather than enforce compliance, and it should be flexible enough to adapt to different company settings.

Phase 3: Design & development

The third research question focused on translating the requirements into a working solution: **“What is the corresponding decision-support tool that integrates the identified requirements to support Dutch high-tech manufacturing companies in implementing the Twin Transition?”**

For this, the De Bruin et al. (2005) maturity model methodology was used as a foundation. The existing Accenture Industry Sustainability Maturity Model was adapted to fit the high-tech manufacturing sector. First, the sustainability dimensions, Environmental, Social, and Governance (ESG), were aligned with the digital transformation dimensions of People, Process, and Policy.

To understand what sustainability impacts are most material in this sector, two sources were used. Environmental impacts were assessed using an Environmentally Extended Input-Output Analysis (EEIOA), focused on Dutch high-tech manufacturing in line with CSRD and ESRS requirements. Social and governance impacts were identified using the MSCI ESG Industry Materiality Map. Then, the most relevant digital manufacturing technologies were mapped to the ESG issues they could influence. Where overlaps occurred between sustainability and digital goals, these intersections were defined as Twin Transition sub-dimensions.

A set of five maturity levels was established, based on existing academic frameworks for digital and data maturity: descriptive, diagnostic, predictive, prescriptive, and adaptive. Technologies were placed along this scale, and their contributions to sustainability goals were assessed at each level. This made it possible to define KPIs that track both the digital and sustainability progress of a company.

Once the maturity model was in place, a next-steps component was added to the decision-support tool. This part of the tool recommends digital technologies tailored to a company's priorities and maturity level. It not only highlights their potential positive impacts on ESG dimensions, but also identifies possible negative side effects and the complexity of implementation. For example, higher maturity levels typically offer greater sustainability benefits (e.g., improved energy efficiency), but require more effort and resources. In some cases, these efforts may even challenge business performance if sustainability priorities are pursued over productivity. With a clear picture of what information was needed to provide tailored recommendations, a Microsoft Forms survey was created to collect the necessary input from companies.

The result is a decision-support tool with three main components, that together translate the requirements from Phase 2 into a practical and usable tool:

1. A survey to gather data on ESG priorities and current maturity levels;
2. A Twin Transition maturity model that visualizes the gap between a company's current and target state across People, Process, and Policy;
3. A dashboard that recommends suitable digital manufacturing technologies, along with information about their ESG benefits, trade-offs, and implementation complexity.

Phase 4: Demonstration & evaluation

Once the prototype was built in the form of a survey and web application, the fourth sub-research question was explored: **“How does the integrated decision-support tool for the Dutch high-tech manufacturing sector perform when demonstrated to intended target users?”**

To test the tool, four guided demonstration sessions were held: three with consultants that work with Dutch high-tech manufacturing clients and one with both a manufacturing engineer and sustainability lead from a Dutch manufacturing company. These sessions showed that the tool helped create a shared understanding between departments and supported conversations around sustainability and digital transformation. Participants described it as useful for creating an initial overview of opportunities and blind spots.

At the same time, feedback from the demonstrations was used to answer the fifth sub-research question: **“How can the proposed decision-support tool be improved, based on the results of the demonstration phase, to ensure that it is an effective decision support tool for the Dutch high-tech manufacturing sector to simultaneously improve its digital and sustainability capabilities?”** Three key improvements were suggested:

1. Integrating the survey and dashboard into a single platform;
2. Providing clearer background information for each recommended technology;
3. Adding return-on-investment analysis and benchmarking features to strengthen the business case.

Answering the main research question

The five sub-research questions provided a clear, step-by-step pathway for answering the main research question. They structured the research from problem identification through tool design to practical validation, ultimately resulting in the development of a decision-support tool that helps Dutch high-tech manufacturers tackle the intertwined challenges of digital transformation and sustainability, in line with the requirements of the CSRD.

The resulting tool is a novel integration of digital maturity assessment and sustainability performance measurement. It brings together three interconnected elements: a survey to capture company-specific ESG priorities and maturity benchmarks, a visual maturity model that maps current capabilities against target states across the dimensions of People, Process, and Policy, and a recommendation overview that identifies relevant digital manufacturing technologies based on sustainability impact and implementation complexity.

From a scientific perspective, this study advances the emerging field of Twin Transition research by addressing critical gaps in the current literature. While existing frameworks often outline high-level aspirations without offering practical guidance, this research delivers a concrete, operational approach that integrates the full ESG scope required by the CSRD. What distinguishes this tool is its explicit recognition that digital transformation and sustainability are not separate transitions, but interconnected socio-technical processes that need to be managed in an integrated way. By directly linking levels of digital maturity to specific Environmental, Social, and Governance outcomes, the tool goes beyond the binary treatment often seen in earlier studies, where digital transformation and sustainability are examined in isolation or only superficially connected.

Methodologically, this research makes an important contribution by showing how Design Science Research can systematically bridge the persistent gap between theory and practice in Twin Transition studies. By applying a complete five-phase DSR approach, this study offers a clear template for translating high-level research insights into practical, usable tools for industry. The integration of quantitative impact assessment through EEIOA with stakeholder-driven requirement definition also represents an advance over earlier approaches that rely either on generic sustainability frameworks or solely on expert judgment without empirical validation.

In addition, this research contributes to the field of Industrial Ecology by offering a more detailed socio-technical perspective on how digital transformation and sustainability interact in advanced industrial contexts. The framework developed here explicitly connects the social (People), technical (Process), and governance (Policy) dimensions of digital manufacturing to their sustainability impacts. This broadens Industrial Ecology's traditional focus on physical resource flows to include the hybrid physical-digital nature of modern industrial systems. A central insight reinforced here is that digital manufacturing technologies are not inherently sustainable or unsustainable: their true impact depends on how they are applied within specific organizational and operational contexts.

From a practical standpoint, the tool's value does not lie in prescribing fixed solutions, but in serving as a facilitator for structured, strategic dialogue within companies. The demonstration sessions confirmed its effectiveness as a "conversation starter," providing a common language for discussing the Twin Transition and helping different departments identify both opportunities and blind spots that might otherwise remain hidden. By bringing sustainability, digital, and operations teams together around shared priorities, the tool helps bridge the awareness-to-action gap.

At the same time, the research underlines important limits. While digital manufacturing technologies can deliver significant efficiency gains (such as reduced energy use per unit, streamlined material flows, and predictive maintenance) they do not resolve the more fundamental challenge of absolute resource consumption. There is also the risk of rebound effects, where increased efficiency drives greater production volumes, offsetting sustainability gains. Moreover, the tool's sector-specific design for Dutch high-tech manufacturing ensures a strong practical fit, but naturally limits its direct transferability to other sectors or countries without adaptation.

Ultimately, the decision-support tool developed through this research provides Dutch high-tech manufacturers with a practical pathway for aligning digital transformation with sustainability goals, translating broad policy ambitions into concrete, context-specific strategies. By creating a shared language for cross-functional collaboration and making trade-offs visible, the tool helps organizations move beyond fragmented efforts toward more integrated transformation approaches.

At the same time, this research reinforces an important point: while digital tools can be powerful enablers, they cannot deliver full sustainability outcomes on their own. True transformation depends on the alignment of data, technology, governance, organizational culture, and evolving policy frameworks. Still, this study demonstrates that a sector-specific decision-support tool can serve as an important stepping stone, helping companies navigate complexity, build internal alignment, and lay the groundwork for the deeper systemic changes needed to achieve both digital excellence and meaningful sustainability performance in today's quickly changing industrial landscape.

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Introduction materials

A.1. Overview of the high-tech manufacturing sub-sector characteristics.

Table A.1: Overview of sub-sector characteristics in high-tech manufacturing. Other Transport Equipment is excluded, as there could be no overall characteristics identified for this aggregated sub-sector.

Sub-sector	Raw Material Transformation	Process Steps (Design → Sourcing → Production → QC)	Use of Machinery vs. Labor	Production Scale & Complexity	Quality Control Focus
Machinery & Equipment	– Transforms mostly metal & optical components into advanced machines. – Heavy use of precision machining (metals) and integration of electronics/optics. – Relies on extensive supplier network for part fabrication (1000s of parts). (van Kappen et al., 2023)	– Intense design/R&D phase (high customization). – Global sourcing of specialized parts, complex supply chain management. – Assembly in cleanrooms for precision equipment (to avoid contamination). – Long calibration & testing cycles for each unit before delivery. (van Kappen et al., 2023; ASML, 2020)	– Automation for component fabrication (CNC, robotics). – Skilled labour for integration & tuning (manual assembly of high-precision modules). – Coordinated teams of engineers/technicians build each machine. (ASML, 2020)	– Low volume, high mix (often made-to-order machines). – Extremely complex products (e.g., lithography machines with 100k parts). – Modular production (different sites build subsystems). (ASML, 2020)	– Ultra-strict quality and cleanliness (ISO 1 cleanrooms for assembly). – 100% functional testing of each machine, extensive calibration. – Traceability of parts, continuous improvement to eliminate defects. (Holland High Tech, 2024)

Sub-sector	Raw Material Transformation	Process Steps (Design → Sourcing → Production → QC)	Use of Machinery vs. Labor	Production Scale & Complexity	Quality Control Focus
Electrical & Electronic Equipment	- Transforms silicon wafers & electronics into chips/devices. - Photolithography, etching etc. to create ICs on wafers (chemical processes). - PCB fabrication and soldering for electronic assemblies. (van Kappen et al., 2023)	- Design and IP-intensive (chip design and PCB design). - Front-end fabrication (wafer processing) taking months per batch. - Back-end assembly of chips (packaging) and system integration of electronics. - Multi-tier testing (wafer test, board test, final device test) throughout. (Rabobank RaboResearch, 2023)	- Highly automated production: wafer fabs use robots in clean-rooms, surface-mount technology lines place components at high speed. - Human labour for oversight, custom assembly, and engineering (especially in prototyping and system integration). - Combination of automated test equipment and skilled operators for QA. (Rabobank RaboResearch, 2023)	- Ranges from mass production (chips) to low-volume high complexity (e.g., defence electronics). - Complexity at micro-scale (billion-transistor chips) and system-scale (complex PCB assemblies). - Globalized supply chain (fabs, assembly plants worldwide) requires coordination. (van Kappen et al., 2023)	- Statistical process control and in-line inspections (microscopic defect control in fabs). - Rigorous final testing of each component/device (ensuring reliability to six-sigma levels). - Compliance with industry standards (e.g., IPC for electronics, automotive AEC-Q for chips), high traceability. (Rabobank RaboResearch, 2023)
Medical Technology	- Works with medical-grade materials (bio-compatible metals, plastics) and electronic parts. - Transforms components via precision assembly into safe, effective medical devices. - Often includes sterilization/clean packaging as part of process. (van Kappen et al., 2023)	- Extensive design & validation upfront (meeting regulatory requirements). - Careful supplier qualification and sourcing of certified materials/parts. - Assembly of devices in controlled environments (clean or sterilized if needed). - Validation testing on devices (environmental, performance, and sometimes clinical tests) before approval. (Philips Healthcare, 2025)	- Mix of automation and manual: automated assembly for disposables and electronics, manual assembly for complex equipment and custom devices. - Skilled technicians perform calibration and final adjustments. - Labor also heavily involved in documentation (every step logged for compliance). (Philips Healthcare, 2025)	- Moderate volume for many products (hundreds to thousands/year), some disposables in high volume. - High complexity due to multi-disciplinary nature (mechanical, electronic, software, biomedical in one). - Long cycle times per unit for large machines (due to testing and certification). (van Kappen et al., 2023)	- Patient safety-oriented QA: ISO 13485 quality system, full traceability of each device. - Rigorous testing of each unit against specifications, long validation cycles. - Regulatory audits and requirements (every device must meet CE/FDA standards, with extensive documentation). (Philips Healthcare, 2023)

Sub-sector	Raw Material Transformation	Process Steps (Design → Sourcing → Production → QC)	Use of Machinery vs. Labor	Production Scale & Complexity	Quality Control Focus
Aerospace	- Transforms aerospace-grade metals & composites into air/spacecraft parts. - Uses 5-axis CNC machining for metals, autoclave curing/advanced welding for composites. - Raw materials are high-spec (e.g., titanium, carbon fiber) with full traceability. (KРАНENDONK Production Systems BV, 2020)	- Design & engineering under certified rules (airworthiness requirements). - Part fabrication (machining, composite layup) with strict process control. - Sub-assembly (riveting, bonding parts into larger structures) in jigs for alignment. - Integration of systems (wiring, hydraulics) and final assembly/testing of modules or full system. - Recurrent inspection at every stage (NDT, dimensional checks, functional tests). (van Kappen et al., 2023)	- Advanced machinery for fabrication (CNC, robots for drilling/welding) where repeatable, but many tasks are manual due to low volume and complexity. - Highly skilled labour (certified aerospace technicians) for assembly, hand layups, inspections, and rework. - Automation used selectively (e.g., robotic composite placement) when it improves quality/efficiency. (KРАНENDONK Production Systems BV, 2020)	- Very low volume (often build-to-order parts for aircraft programs). - Extremely high complexity and customization (each part must meet tight specs and integrate into larger aircraft). - Long lead times, essentially project manufacturing. (KРАНENDONK Production Systems BV, 2020)	- Zero-defect mindset (flight safety critical). - Extensive NDT inspections (ultrasound, X-ray) on structures, every part certified. - Quality management via AS9100, each product comes with full documentation and must pass stringent acceptance tests (including test flights or simulations). (KРАНENDONK Production Systems BV, 2020)

A.2. Overview of Industry 4.0 technologies and their sustainability

Table A.2: Overview of the potential sustainability opportunities and potential negative sustainability impacts of Industry 4.0 technologies for the manufacturing sector across the triple bottom line dimensions.

Technology	Definition	Sustainability Opportunities			Sustainability Impacts		
		Environmenta	Social	Economic	Environmenta	Social	Economic
Industrial Internet of Things (IIoT) & Cyber-Physical Systems	Connected sensors and devices that communicate via the Internet (Sartal et al., 2020)	Improves energy use visibility (Sartal et al., 2020)	Enhances safety with real-time hazard alerts (Sartal et al., 2020)	Reduces operational costs with automation (Matin et al., 2023)	High energy consumption (Matin et al., 2023)	Job displacement for untrained workers (Jamwal et al., 2021)	High setup and maintenance costs (Jamwal et al., 2021)
		Extends equipment lifespan (Sartal et al., 2020)	Increases worker safety through focused maintenance (Sartal et al., 2020)		E-waste from outdated sensors (Matin et al., 2023)		

Technology	Definition	Sustainability Opportunities			Sustainability Impacts		
		Environmenta	Social	Economic	Environmenta	Social	Economic
Autonomous & Collaborative Robots	Robots that operate independently and work safely with humans (Sartal et al., 2020)	Reduces material waste through precision (Jamwal et al., 2021)	Reduces workload and injuries from repetitive tasks (Sartal et al., 2020)	Boosts productivity and reduces downtime (Bai et al., 2020)	Significant energy consumption in production and use (Jamwal et al., 2021)	Job displacement for manual roles (Jamwal et al., 2021)	High upfront and integration costs (Jamwal et al., 2021)
		Minimizes energy use for specific tasks (Jamwal et al., 2021)	Improves workplace safety (Jamwal et al., 2021)		Disposal adds to e-waste (Jamwal et al., 2021)		
Simulation Systems & Virtualization	Virtual models simulate and optimize real-world processes (Sartal et al., 2020; Bai et al., 2020)	Lowers energy use by testing virtually before physical implementation (Sartal et al., 2020)	Enhances training in safe virtual environments (Sartal et al., 2020)	Reduces costs from errors and downtime (Bai et al., 2020)	High energy requirements for complex simulations (Jamwal et al., 2021)	Over-reliance may limit hands-on skills (Jamwal et al., 2021)	High investment in software, hardware, and expertise (Bai et al., 2020)
		Reduces rejection rates (Sartal et al., 2020)	Improves worker safety (Bai et al., 2020)				
Cloud Computing	Virtual computing and storage services accessible via the Internet (Sartal et al., 2020)	Saves energy by consolidating resources in virtualized data centres (Sartal et al., 2020)	Expands access to advanced technology (Jamwal et al., 2021)	Lowers physical resource costs (Sartal et al., 2020)	High carbon footprint from energy-intensive data centres (Bai et al., 2020)	Data breaches may affect trust (Jamwal et al., 2021)	Ongoing subscription fees (Jamwal et al., 2021)
			Facilitates collaboration (Jamwal et al., 2021)				
Additive Manufacturing (AM)	Produces components layer-by-layer, including 3D printing (Sartal et al., 2020)	Minimizes material waste (Kopeinig et al., 2024)	Enables customization for specific user needs (Jamwal et al., 2021)	Speeds up prototyping (Sartal et al., 2020)	High energy use for some materials (Jamwal et al., 2021)	Potential loss of manual jobs (Bai et al., 2020)	High initial investment costs (Bai et al., 2020)
		Increases machinery lifespan by repairing worn parts (Bai et al., 2020)		Cost reduction for low-volume production (Jamwal et al., 2021)			

Technology	Definition	Sustainability Opportunities			Sustainability Impacts		
		Environmenta	Social	Economic	Environmenta	Social	Economic
Blockchain Technology	Distributed database enabling secure, transparent record-keeping (Kopeinig et al., 2024; Bai et al., 2020)	Improves waste management with material tracking (Kopeinig et al., 2024; Bai et al., 2020)	Promotes transparency and fairness (Bai et al., 2020)	Reduces inefficiencies in logistics and fraud (Matin et al., 2023)	Energy-intensive implementations (e.g., proof-of-work systems) (Matin et al., 2023)		High integration and operational costs (Jamwal et al., 2021)
			Enhances trust in supply chains (Bai et al., 2020)				
AI & Big Data Analytics	Analyses large datasets to identify patterns and support decisions (Kopeinig et al., 2024)	Optimizes resource use and reduces inefficiencies (Kopeinig et al., 2024; Bai et al., 2020)	Enhances collaboration and employee well-being (Bai et al., 2020)	Boosts productivity and reduces downtime (Jamwal et al., 2021; Bai et al., 2020)	High energy consumption for data processing (Matin et al., 2023)	Privacy concerns if data is misused (Matin et al., 2023)	High implementation costs (Matin et al., 2023)
		Supports predictive maintenance (Kopeinig et al., 2024)	Improves decision-making (Matin et al., 2023)				

B

Phase 1 materials

B.1. Literature review

B.1.1. Structured review: the PRISMA approach for identifying research articles

The structured literature review follows the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) methodology for selecting papers. PRISMA provides a structured framework that ensures transparency, completeness, and reproducibility in structured reviews (Page et al., 2021).

The study selection process follows a phased approach, beginning with the definition of key search terms and the selection of suitable databases. Subsequently, relevant records from various bibliographic databases are identified, followed by a screening phase where duplicate records and irrelevant studies are excluded. The eligibility phase then involves the assessment of articles to determine their alignment with the research focus. Finally, the inclusion phase results in the selection of studies that provide valuable insights into the challenges of implementing the Twin Transition.

Identification

To ensure comprehensiveness, the literature search is conducted using two major academic databases: Scopus and Web of Science. These databases were chosen for their extensive coverage of peer-reviewed literature across multiple disciplines. Other databases were not included, as Scopus and Web of Science already provide broad and overlapping coverage of high-quality, peer-reviewed sources relevant to the research topic, making their use both sufficient and methodologically sound for a scientifically rigorous review. While Scopus offers enriched citation analytics and broad subject coverage, Web of Science provides access to a diverse range of research outputs, including conference proceedings and book reviews (Elsevier, 2025; Clarivate, 2025). The combination of both databases ensures that no relevant research is overlooked, thereby strengthening the robustness of the structured review (Wageningen University & Research, 2025).

To address the sub-research question on the challenges the manufacturing sector faces in progressing with the Twin Transition, search terms were developed using official EU publications on the Twin Transition (Muench et al., 2022; European Investment Bank, 2021). Two types of search terms were used. Term type 1 contains the subject of the sub-research question: the Twin Transition. As this is a new phenomenon, multiple synonyms or other terms to address the simultaneous digital and sustainability transitions are found in the literature. Term type 2 contains the domain of the sub-research question: the manufacturing sector. An overview of these two term types can be found in Table B.1.

The search was conducted using the Boolean operator OR between different strings within a term type (e.g., "Twin Transition" OR "Twin transformation"). Between the term types, the Boolean operator AND was used to specify the search results (e.g., "Twin Transition" AND "Manufacturing").

During the identification phase, 174 research articles were identified using Scopus and Web of Science presented 745 research papers following the keyword search. The Scopus search was completed between 13 and 14 February 2025, while the Web of Science search was completed between 18 and 19 February 2025.

Term type 1: subject	Term type 2: domain
Twin transition	Manufactur*
Twin transformation	Production
Dual transition	Industrial*
Dual transformation	
Green-digital nexus	
Green-digital transition	
Green-digital transformation	

Table B.1: Search terms used for the structured review to identify challenges experienced by manufacturing companies in advancing in the Twin Transition simultaneously. The search terms for the Twin Transition were based on official EU publications addressing the concept of the Twin Transition (Muench et al., 2022; European Investment Bank, 2021).

Screening

The screening phase is designed to refine the search results. Predefined criteria were applied to titles, abstracts, and keywords. These criteria ensured that only relevant papers would be processed at a later stage in the research.

During the screening phase, three basic criteria were applied. Firstly, research articles needed to be accessible through university or Accenture resources to assess the full text. Next to that only papers that are written in English were included. Regarding publication date, only research articles from 2020 onwards were included, as Gartner stated that the development of advanced digital technologies is 5-10 years ahead compared to practical implementation in the manufacturing sector (Shikanai et al., 2024). As a result, literature older than five years is likely to reflect technological contexts and challenges that are outdated and no longer aligned with current industry realities. By focusing on more recent publications, this review ensures that the identified challenges and insights are reflective of the current technological landscape.

During the screening phase, the number of identified research articles was reduced to 844 papers that matched the three basic criteria. After removing duplicates, 483 research articles were left.

Eligibility

Following the screening phase, the eligibility assessment further refines the selection of studies by applying more specific content-related criteria. For this, three types of content-related criteria were applied to the titles, abstracts and keywords.

The first criterion was exclusion based on the subject. Research articles had to refer to the Twin Transition in the sense of a simultaneous digital and sustainability transformation. If the Twin Transformation referred to another type of simultaneous transition, the research article was excluded. For example, the Twin Transition sometimes refer to a simultaneous demographic and economic transition in a country. The second criterion was exclusion based on relevance to the domain. The paper needed to apply to the manufacturing sector and include or apply to industrial production. The third criterion was exclusion based on science domain. Research articles should not be overly technical or only have a social focus. They needed to be interdisciplinary and fit the socio-technical scope of the research. Applying these refinement criteria reduced the number of relevant papers to 37.

A second round of eligibility assessment was conducted to refine the number of papers selected based on the full text using the same criteria, which further reduced the number of relevant research articles to 34. An overview of the authors, titles and focus of each of these research articles can be found in Appendix B.1, Table B.2.

Included

The final set of 34 papers met all inclusion criteria and served as the foundation for the structured analysis in this chapter.

B.1.2. Structured review: identified academic literature

Table B.2: Overview of the selected papers with title and focus summary.

Authors	Publication year	Title and Focus
Del Vecchio et al. (2025)	2025	Circular value creation and business process management for the Twin Transition: The case of an energy company. The article examines how the Twin Transition drives strategic and operational changes in manufacturing, using a case study to show how digital technologies enable the circular economy and green transformation.
Abilakimova et al. (2025)	2025	Systematic literature review of digital and green transformation of manufacturing companies in Europe. The article reviews the Twin Transition in European manufacturing SMEs, identifying barriers, enablers, and readiness frameworks through a systematic literature review. It proposes a strategic framework to guide companies through digital and green transformation stages.
Trevisan et al. (2024)	2024	Skills for the Twin Transition in manufacturing: A systematic literature review. The article explores the critical skills needed for a successful Twin Transition in manufacturing, identifying 40 key competencies across resilience, digital technologies, and specialized skills.
Madreiter et al. (2024)	2024	Sustainable Maintenance: What are the key technology drivers for ensuring Positive Impacts of Manufacturing Industries? The article explores how Industry 4.0 technologies enable sustainable maintenance in manufacturing, reducing resource use, waste, and emissions.
Sjödin et al. (2024)	2024	Conceptualizing ecosystem management capabilities: Managing the ecosystem-organization interface. The article explores how manufacturers navigate the Twin Transition by developing ecosystem foresight, integration, and governance capabilities.
Gulbrandsen-Dahl et al. (2024)	2024	Introduction. The chapter introduces research from the SFI Manufacturing centre, outlining the evolution of key topics in Norway's manufacturing industry. It categorizes research into eight areas, including digitalization and sustainability, reflecting industrial partners' priorities.
Stucki et al. (2024)	2024	Data driven value creation in industrial services including remanufacturing. The article explores how data-driven product-service systems, including remanufactured products, can create sustainable value in the context of the Twin Transition.
Spaltini et al. (2024a)	2024	Toward a technology roadmapping methodology to enhance sustainable and digital transition in manufacturing. The paper proposes a methodology to guide companies in integrating sustainability and business objectives through Industry 4.0 and process management.
Spaltini et al. (2024b)	2024	Development and implementation of a road mapping methodology to support Twin Transition at manufacturing plant level. The paper proposes a roadmapping methodology to guide manufacturing companies through the Twin Transition linking strategic goals to operational activities. It identifies 39 barriers to implementation at micro, meso, and macro levels, demonstrating the methodology's effectiveness.
Perossa et al. (2023)	2023	Twin Transition cosmetic roadmapping tool for supporting cosmetics manufacturing. The paper presents the Twin Transition Cosmetic Roadmapping Tool, designed to help cosmetics companies assess and improve their digital and sustainable transformation.
Chen et al. (2023)	2023	Enabling the Twin Transition: Digital technologies support environmental sustainability through lean principles. The paper explores how lean production, combined with digital technologies like IoT, can drive environmental sustainability in manufacturing.
Kürpick et al. (2023)	2023	An integrative view of the transformations towards sustainability and digitalization: The case for a dual transformation. The paper identifies challenges, barriers, and opportunities in the dual transformation of digitalization and sustainability in manufacturing. Through expert interviews, it develops a framework to help companies address the interdependencies and synergies of both transitions.
Kürpick et al. (2024)	2024	Capabilities for the Strategic Alignment of Sustainability and Digitalization in Manufacturing: Insights from Theory and Practice. The paper identifies 26 socio-technical capabilities essential for aligning digitalization and sustainability in manufacturing. Through a literature review and expert interviews, it provides a reference model to guide companies in strategically managing the dual transformation.

Authors	Publication year	Title and Focus
Kren and Lawless (2024)	2024	Firm-level attitudes and actions to the “Twin Transition” challenges of digitalisation and climate change. The paper examines the overlap between climate actions and digitalization in firms, finding many have both plans in place but a gap between attitudes and actual implementation.
Re et al. (2024)	2024	Managing Open Twin Transition in SMEs: A Case Study in the Fashion Industry. The paper explores how companies in the fashion industry can navigate the Twin Transition by adopting open innovation approaches, focusing on the shift from internal R&D to collaboration with external partners. It highlights challenges in digitalization and sustainability.
Chatzistamoulou (2023)	2023	Is digital transformation the Deus ex Machina towards sustainability transition of the European SMEs? The paper examines how digital transformation and public procurement participation support SMEs’ sustainability transitions in the EU.
Kekkonen et al. (2023)	2023	Stepping towards the green transition: challenges and opportunities of Estonian companies. The paper examines Estonian entrepreneurs’ perceptions of the Twin Transition, revealing that innovation and stakeholder pressure help turn the challenges of digital and green transitions into opportunities for sustainability.
Tabares et al. (2025)	2025	Twin Transition in industrial organizations: Conceptualization, implementation framework, and research agenda. This paper examines the Twin Transition, integrating digital and green transformations, and the challenges firms face in aligning these with sustainability goals. It introduces a framework for implementing the Twin Transition, highlighting key practices and success factors.
Breiter et al. (2024)	2024	Dynamic capabilities for the Twin Transformation climb: A capability Maturity Model. This article develops a Twin Transformation capability maturity model to guide organizations in integrating digital and sustainability transformations. Based on literature and expert interviews, it identifies three pathways for firms to become twin transformers.
Findik et al. (2023)	2023	Industry 4.0 as an enabler of circular economy practices: evidence from European SMEs. This study explores the synergy between Industry 4.0 technologies and circular economy practices among European SMEs.
Diodato et al. (2023)	2023	Introduction to the special issue on “the Twin (digital and green) Transition: handling the economic and social challenges”. This special article examines the Twin Transition and its impact on industrial innovation and societal inequalities.
Fouquet, R., & Hippe, R.	2022	Twin Transition of decarbonisation and digitalisation: A historical perspective on energy and information in European economies. This paper explores the Twin Transition of decarbonization and digitalization in European economies and emphasizes the need for balanced structural transformation in the manufacturing industry to avoid a high-carbon future while promoting synergies between these transitions.
Sassanelli et al. (2024)	2024	Stakeholder engagement models in digital-enabled circular manufacturing ecosystems. This paper explores how digital technologies and stakeholder engagement support circular manufacturing, highlighting Industry 4.0’s role in integrating sustainability into business models.
Benedetto and Forleo (2024)	2024	PDO Economy and Quality Agri-Food District in the wine sector: Blockchain and digitalization as tools for the Twin Transition. This paper examines how blockchain and digital technologies can support the Twin Transition in the wine sector, focusing on their potential to enhance sustainability in PDO quality districts while addressing implementation challenges.
Elyasi et al. (2024)	2024	Use of AI in assembly line design and worker and equipment management: review and future directions. This paper examines AI’s role in enhancing efficiency, adaptability, and sustainability in manufacturing, particularly within assembly lines, equipment selection, and workforce management.
Christmann et al. (2024)	2024	The Twin Transformation butterfly: Capabilities for an integrated digital and sustainability transformation. This paper conceptualizes “Twin Transformation” as the synergistic interplay between digital and sustainability transformations, enhancing organizational performance and value creation. It introduces a capability framework based on dynamic capability theory.
Fu and Xu (2024)	2024	The impact of digital technology on enterprise green innovation: quality or quantity? This paper examines how digital technology drives the Twin Transition of digitalization and green innovation in Chinese enterprises.

Authors	Publication year	Title and Focus
Benedetti et al. (2023)	2023	Digitalization in Europe: A potential driver of energy efficiency for the Twin Transition policy strategy. This paper investigates the impact of digitalization on energy efficiency in Europe, analyzing the European Twin Transition by mapping the Digital Economy and Society Index (DESI) and its sub-indices against energy productivity.
Kirov (2023)	2023	Decent, inclusive, and green? Mission impossible? This article examines the Twin Transition by analyzing the role of digitalization in Sofia's regional ICT ecosystem, highlighting its disconnection from the green transition and the need for policy intervention to align both processes.
Sareen et al. (2023)	2023	Social implications of energy infrastructure digitalisation and decarbonization. This article explores how digitalization in energy infrastructure interacts with decarbonization and social inclusion.
Peças et al. (2023)	2023	Holistic framework to data-driven sustainability assessment. This paper proposes a holistic framework to help companies assess sustainability performance, combining data-driven approaches with sustainability assessments and continuous improvement methods.
Korucuk et al. (2022)	2022	Assessing green approaches and digital marketing strategies for the Twin Transition via fermatean fuzzy SWARA-COPRAS. This paper develops a decision model combining green approaches and digital marketing strategies for ICTs in the logistics sector, using a hybrid methodology to evaluate strategies that balance sustainability, digital transformation, and economic factors.
Rahnama et al. (2022)	2022	Collaboration in value constellations for sustainable production: The perspective of small technology solution providers. This paper explores the challenges small technology solution providers face in developing sustainable production solutions for manufacturing customers.
Ortega-Gras et al. (2021)	2021	Twin Transition through the implementation of industry 4.0 technologies: Desk-research analysis and practical use cases in Europe. This paper analyzes European policies and practical use cases related to the adoption of Key Enabling Technologies that drive both Industry 4.0 and the Circular Economy transition.

B.1.3. Overview of challenges identified per author

Table B.3: Overview of identified challenges per author.

Author	Challenges												
	1. High investment costs	2. Uncertainty in economic returns	3. Lack of impacts understanding	4. Lack of example transition paths	5. Lack of tailored to different starting points	6. Evolving nature of Twin Transition	7. Lack of quantification	8. Skill training	9. Resistance against change	10. Reorganisation structure	11. Lack of focus on social sustainability	12. Changing and double regulation	13. Compliance and competitiveness
Del Vecchio et al. (2025)		X				X			X	X			
Abilakimova et al. (2025)					X	X	X			X	X	X	
Trevisan et al. (2024)				X		X		X		X			
Sjödén et al. (2024)	X					X				X			X

Author	Challenges												
	1. High investment costs	2. Uncertainty in economic returns	3. Lack of impacts understanding	4. Lack of example transition paths	5. Lack of tailored to different starting points	6. Evolving nature of Twin Transition	7. Lack of quantification	8. Skill training	9. Resistance against change	10. Reorganisation structure	11. Lack of focus on social sustainability	12. Changing and double regulation	13. Compliance and competitiveness
Gulbrandsen-Dahl et al. (2024)	X	X						X	X				
Stucki et al. (2024)	X	X	X							X			
Spaltini et al. (2024a)		X	X		X	X	X			X			
Spaltini et al. (2024b)		X	X									X	X
Perossa et al. (2023)				X									
Chen et al. (2023)	X			X		X							
Kürpick et al. (2023)					X	X	X	X	X				
Kürpick et al. (2024)			X		X		X		X				
Kren and Lawless (2024)			X			X	X	X				X	
Re et al. (2024)			X							X		X	
Chatzistamoulou (2023)		X	X	X		X						X	
Kekkonen et al. (2023)	X	X	X			X	X						
Tabares et al. (2025)		X				X	X	X		X		X	
Breiter et al. (2024)	X					X		X					
Findik et al. (2023)						X	X		X				
Diodato et al. (2023)				X				X					
Fouquet and Hippe (2022)	X	X					X	X					
Sassanelli et al. (2024)							X	X					
Benedetto and Forleo (2024)			X						X				

Author	Challenges												
	1. High investment costs	2. Uncertainty in economic returns	3. Lack of impacts understanding	4. Lack of example transition paths	5. Lack of tailored to different starting points	6. Evolving nature of Twin Transition	7. Lack of quantification	8. Skill training	9. Resistance against change	10. Reorganisation structure	11. Lack of focus on social sustainability	12. Changing and double regulation	13. Compliance and competitiveness
Elyasi et al. (2024)	X	X	X										
Christmann et al. (2024)								X	X		X		
Fu and Xu (2024)	X							X					
Benedetti et al. (2023)	X			X		X							
Kirov (2023)				X		X		X			X		
Sareen et al. (2023)									X	X	X		
Peças et al. (2023)			X				X						
Rahnama et al. (2022)		X											
Ortega-Gras et al. (2021)	X		X	X									

Table B.4: Identified challenges of implementing the Twin Transition in manufacturing per paper and the authors' interpretation of the challenge.

Research paper	Challenge with number	Descriptive summary
Del Vecchio et al. (2025)	3. The sustainability impact of digital technologies remains poorly understood by manufacturing companies.	The article argues that there is a lack of a comprehensive model that integrates the features of digital transformation and green transition. This suggests that there is still insufficient insight into how digitalization specifically contributes to the different aspects of sustainability.
Del Vecchio et al. (2025)	7. Unquantified decisions within the Twin Transition complicate long-term decision-making.	The article discusses the importance of Key Performance Indicators (KPIs) to characterize complex energy systems. The lack of concrete data and measurement methods makes it difficult to measure the impact of the Twin Transition and to make the right decisions about investments.
Del Vecchio et al. (2025)	10. The Twin Transition may necessitate organizational restructuring, such as increased collaboration.	The Twin Transition is described as a change that affects the strategic and organizational configuration of companies and requires innovation of their business model. The article emphasizes the need to promote virtual mechanisms of collaboration between companies and research institutions, as well as the active involvement of the community of stakeholders.
Del Vecchio et al. (2025)	11. There is insufficient focus on social sustainability within the Twin Transition, as the link between environmental sustainability and digitalization is clearer.	The article mentions that the complexity of the transition requires expertise in technology (digital and green), management challenges and social aspects. It is stated that a stronger focus on social sustainability would be a valuable addition.

Research paper	Challenge with number	Descriptive summary
Abilakimova et al. (2025)	5. Manufacturing companies lack tailored strategies that address their unique starting points in each of the Twin Transition.	Current assessment tools are generic and not tailored to the specific characteristics of companies, regardless of their size or type of production. Companies differ in their digital and green readiness.
Abilakimova et al. (2025)	6. The evolving nature of the Twin Transition adds complexity to their implementation for manufacturing companies.	The Twin Transition each involve evolving domains: in the digital transition, new technologies are constantly being developed and can be implemented, while in the sustainability transition, new impacts are continuously emerging in supply chains. This makes it challenging to predict the most effective implementation strategy.
Abilakimova et al. (2025)	7. Unquantified decisions within the Twin Transition complicate long-term decision-making.	Manufacturers are struggling to measure their performance on digital and green initiatives and therefore to make progress in the Twin Transition measurable.
Abilakimova et al. (2025)	10. The Twin Transition may necessitate organizational restructuring, such as increased collaboration.	Successful Twin Transition requires fundamental changes in thinking about industrial processes, supply chain management and service delivery. Integration of information from different areas and collaboration, both within organizations and with partners in the supply chain, are critical components of a successful Twin Transition.
Abilakimova et al. (2025)	11. There is insufficient focus on social sustainability within the Twin Transition, as the link between environmental sustainability and digitalization is clearer.	Companies often overlook social sustainability in favor of economic and environmental sustainability, especially with digitalization as a driver for sustainability.
Abilakimova et al. (2025)	13. Managing regulations related to the Twin Transition domains while remaining competitive is difficult.	Manufacturing companies are under pressure to meet environmental demands while remaining competitive. Successful strategies require managing multiple processes, stakeholders and regulatory compliance.
Trevisan et al. (2024)	4. There is a shortage of clear, practice-based examples of example transition pathways for the Twin Transition.	There is a lack of clear, practice-based examples of example transition paths for the Twin Transition. This means that companies that want to make this transformation are often in the dark about how to do it concretely. The lack of concrete examples makes it difficult to choose the right strategies and technologies, and to determine the necessary investments.
Trevisan et al. (2024)	6. The evolving nature of the Twin Transition adds complexity to their implementation for manufacturing companies.	The ever-changing nature of the Twin Transition makes implementation more complex for manufacturing companies. Technological developments and new insights into sustainability ensure that the requirements and possibilities are constantly changing.
Trevisan et al. (2024)	8. The Twin Transition demands new skills from both the company and its employees.	The Twin Transition require new skills from both the company and its employees. This includes digital technologies, resilience and specialized skills. For example, employees need to learn to work with new software and machines and need to be able to analyze and interpret data.
Trevisan et al. (2024)	10. The Twin Transition may necessitate organizational restructuring, such as increased collaboration.	The Twin Transition may necessitate organizational restructuring, such as increased collaboration. Implementing the Twin Transition often requires different departments within a company to work more closely together. This can lead to changes in the organizational structure, and to new roles and responsibilities for employees.
Sjödén et al. (2024)	1. The high implementation costs of both the digital and sustainability aspects of the Twin Transition present a significant barrier.	Adopting new technologies and digital solutions requires significant investment. The sources highlight that adopting advanced technologies, often required for both digital and sustainable transformations, requires significant investment. This can be a barrier, especially for smaller manufacturers or companies already facing tight budgets.
Sjödén et al. (2024)	6. The evolving nature of the Twin Transition adds complexity to their implementation for manufacturing companies.	The Twin Transition are a relatively new phenomenon, which increases the complexity for manufacturing companies. The need to respond adequately to changes in the environment, such as new technologies and changing market conditions, requires dynamic capabilities. This means that companies must not only invest in new technologies, but also in developing the ability to quickly adapt and respond to changing circumstances.

Research paper	Challenge with number	Descriptive summary
Sjodin et al. (2024)	10. The Twin Transition may necessitate organizational restructuring, such as increased collaboration.	The Twin Transition require new forms of collaboration and partnerships. The ability to integrate internal functions and collaborate with external partners is essential. This can be a challenge for companies that traditionally operate in silos or are not experienced in strategic partnerships. It requires a shift in the way companies think about their role in the value chain and how they create value.
Sjodin et al. (2024)	13. Managing regulations related to the Twin Transition domains while remaining competitive is difficult.	The article highlights the importance of understanding the ecosystems in which companies operate. This includes navigating the complexity of different standards, regulations and legislation. Manufacturers must keep up to date with the latest developments in sustainability and digital technologies, and ensure they comply with all relevant regulations.
Gulbrandsen-Dahl et al. (2024)	1. The high implementation costs of both the digital and sustainability aspects of the Twin Transition present a significant barrier.	Implementing new technologies, which are often expensive, can be a significant barrier, especially for manufacturers with limited budgets. This applies not only to the initial investment costs, but also to the costs associated with the implementation, operation and maintenance of the solutions.
Gulbrandsen-Dahl et al. (2024)	2. There is a lack of understanding in what the economic returns will be when implementing measures for the Twin Transition.	There is often a lack of clarity around the economic benefits of digitalization, which makes companies reluctant to invest in digital technologies. This can be due to immaturity of technologies or limited understanding of the actual benefits of the technology. The lack of clarity around the economic benefits can be a barrier to pursuing ideas, limiting an organization's ability to identify relevant technology solutions.
Gulbrandsen-Dahl et al. (2024)	8. The Twin Transition demands new skills from both the company and its employees.	A lack of knowledge or competence regarding the development, implementation and/or use of digital technologies can pose a significant barrier to digitalization and limit the organization's ability to fully utilize new digital solutions.
Gulbrandsen-Dahl et al. (2024)	9. Resistance from employees may arise due to the extensive changes required by the Twin Transition	Resistance to change can exist at all levels of a company. This resistance can manifest itself in unreasonable focus on negative aspects of the technology, which can lead to rejection of the business case.
Stucki et al. (2024)	1. The high implementation costs of both the digital and sustainability aspects of the Twin Transition present a significant barrier.	The paper highlights that the financial burden of integrating both digital and sustainable technologies is substantial. Companies often struggle with the upfront investments required for new digital infrastructures, energy-efficient machinery, and compliance with sustainability regulations. These costs can be particularly challenging for small and medium-sized enterprises (SMEs), which may lack the necessary financial resources.
Stucki et al. (2024)	2. There is a lack of understanding in what the economic returns will be when implementing measures for the Twin Transition.	Many firms hesitate to adopt Twin Transition measures due to uncertainties regarding their economic benefits. The paper notes that companies face difficulties in quantifying the return on investment for digital and sustainable technologies, making decision-making riskier. This uncertainty can lead to reluctance in fully committing to transition strategies.
Stucki et al. (2024)	3. The sustainability impact of digital technologies remains poorly understood by manufacturing companies.	Manufacturing companies often struggle to assess how digital technologies contribute to or hinder sustainability goals. While digital solutions can enhance efficiency and reduce waste, their overall environmental impact, such as increased energy consumption from data centers and electronic waste, remains unclear to many businesses.
Stucki et al. (2024)	10. The Twin Transition may necessitate organizational restructuring, such as increased collaboration.	Implementing the Twin Transition often requires changes in organizational structures, including greater collaboration across departments and with external stakeholders. The paper emphasizes that companies may need to support cross-functional cooperation to successfully integrate digital and sustainability efforts.
Spaltini et al. (2024a)	2. There is a lack of understanding in what the economic returns will be when implementing measures for the Twin Transition.	The paper notes that while Industry 4.0 (I4.0) technologies are well understood in theory, their practical applications and economic benefits remain unclear. Manufacturers struggle to align economic and environmental objectives with technological needs. Many Twin Transition initiatives fail due to poor planning and prioritization.

Research paper	Challenge with number	Descriptive summary
Spaltini et al. (2024a)	3. The sustainability impact of digital technologies remains poorly understood by manufacturing companies.	The literature recognizes that digital technologies can enable sustainability, but companies lack structured models to integrate Industry 4.0 with circular economy principles effectively. This knowledge gap hinders adoption and prevents manufacturers from realizing sustainability benefits.
Spaltini et al. (2024a)	5. Manufacturing companies lack tailored strategies that address their unique starting points in each of the Twin Transition.	Companies face difficulties in balancing short- and long-term goals when adopting TT strategies. Many strategies fail due to a lack of alignment between digitalization and sustainability, as well as the absence of methodologies that cater to the specific needs of different manufacturers.
Spaltini et al. (2024a)	6. The evolving nature of the Twin Transition adds complexity to their implementation for manufacturing companies.	The paper emphasizes that TT is a dynamic process requiring continuous adaptation. Companies need methodologies to anticipate technology trends, support decision-making, and manage resource allocation. Without structured guidance, manufacturers struggle with the fast-paced evolution of both digital and sustainability transitions.
Spaltini et al. (2024a)	7. Unquantified decisions within the Twin Transition complicate long-term decision-making.	Many manufacturers lack categorization methods to structure TT projects. This uncertainty makes it difficult to define priorities, assess financial feasibility, and establish a clear roadmap for implementation. Decision-making is further complicated by the absence of economic and sustainability impact evaluations.
Spaltini et al. (2024a)	10. The Twin Transition may necessitate organizational restructuring, such as increased collaboration.	Implementing TT often requires changes in strategies, organizational models, infrastructure, and workforce management. Companies must integrate technological and managerial transformations while ensuring cross-functional collaboration. The paper proposes a technology road mapping methodology to facilitate this integration.
Spaltini et al. (2024a)	2. There is a lack of understanding in what the economic returns will be when implementing measures for the Twin Transition.	There is a lack of insight into the economic benefits of implementing Twin Transition measures. The authors argue that companies lack transparency about the economic impact of sustainability initiatives. This makes it difficult for companies to justify the investments and make the right decisions.
Spaltini et al. (2024a)	3. The sustainability impact of digital technologies remains poorly understood by manufacturing companies.	The sustainability impact of digital technologies is not sufficiently understood by manufacturing companies. This makes it difficult to select and implement the right technologies to support the transition.
Spaltini et al. (2024a)	12. Navigating the dual and evolving regulations governing the Twin Transition presents an added challenge.	Navigating the dual and evolving regulations surrounding Twin Transition poses an additional challenge. Companies must stay on top of the various regulations and ensure they are compliant.
Spaltini et al. (2024a)	13. Managing regulations related to the Twin Transition domains while remaining competitive is difficult.	Managing regulations related to the Twin Transition domains while maintaining a competitive position is difficult. Companies must strike a balance between complying with regulations and maintaining their competitive advantage.
Perossa et al. (2023)	4. There is a shortage of clear, practice-based examples of example transition pathways for the Twin Transition.	A lack of universally accepted example transition pathways is a challenge. The analysis of existing works revealed that most do not provide concrete guidelines for implementation. Some are theoretical or generic and not specific for certain industries.
Chen et al. (2023)	1. The high implementation costs of both the digital and sustainability aspects of the Twin Transition present a significant barrier.	The adoption of both digital and sustainable technologies requires substantial financial investment. Manufacturing companies struggle with the costs associated with upgrading infrastructure, integrating digital tools, and adopting environmentally friendly practices. The dual investment in both digitalization and sustainability can strain financial resources and delay implementation.
Chen et al. (2023)	4. There is a shortage of clear, practice-based examples of example transition pathways for the Twin Transition.	There is a shortage of well-documented, practice-based examples of how companies can successfully navigate the Twin Transition. Without example frameworks or case studies, manufacturing firms face uncertainty in planning and executing their transformation strategies. This lack of guidance makes it difficult for companies to benchmark their progress and adopt best practices.

Research paper	Challenge with number	Descriptive summary
Chen et al. (2023)	6. The evolving nature of the Twin Transition adds complexity to their implementation for manufacturing companies.	The quick development of digital technologies and shifting sustainability regulations create a moving target for manufacturers. Companies must continuously adapt to new technological advancements and evolving regulatory requirements, making long-term planning and investment decisions more complex. This uncertainty adds an extra layer of difficulty in achieving a balanced and effective transition.
Kürpick et al. (2023)	5. Manufacturing companies lack tailored strategies that address their unique starting points in each of the Twin Transition.	There are not many specific strategies that are aligned to their unique starting positions of manufacturers in both sustainability and digitalization. It is important to note that the two strategies (sustainability and digitalization) are often separate rather than integrated, which makes implementation difficult.
Kürpick et al. (2023)	6. The evolving nature of the Twin Transition adds complexity to their implementation for manufacturing companies.	The dynamic and constantly evolving nature of these transitions adds complexity to implementation. The continuous developments in both sustainability practices and digital technologies require a flexible and adaptable approach.
Kürpick et al. (2023)	7. Unquantified decisions within the Twin Transition complicate long-term decision-making.	Decisions made during Twin Transition are often not quantified, which complicates long-term decision-making processes. This can lead to uncertainty and risks when investing in sustainability and digitalization initiatives.
Kürpick et al. (2023)	8. The Twin Transition demands new skills from both the company and its employees.	The Twin Transition require both the company and its employees to develop new skills. A lack of expertise in sustainability or digitalization within the company can hinder the process, possibly requiring external experts.
Kürpick et al. (2023)	9. Resistance from employees may arise due to the extensive changes required by the Twin Transition.	The extensive changes required by the Twin Transition can lead to employee resistance. Successfully navigating the transformation requires continuous support from top management, ensuring that all employees are well-informed and motivated to contribute to the sustainability goals.
Kürpick et al. (2024)	3. The sustainability impact of digital technologies remains poorly understood by manufacturing companies.	Many companies do not see digitalization and Industry 4.0 as opportunities to improve sustainability. There is a lack of knowledge about how sustainability can be integrated into strategic planning of companies. Furthermore, the effect of digitalization on energy consumption on a macroeconomic scale depends on factors such as sector growth, changes in energy efficiency, economic growth and changes in sector structure.
Kürpick et al. (2024)	5. Manufacturing companies lack tailored strategies that address their unique starting points in each of the Twin Transition.	Manufacturing companies lack strategies that are tailored to their unique starting position in the Twin Transition. For example, small and medium-sized enterprises (SMEs) lack knowledge about decarbonization. There is a lack of a clear implementation strategy for the decarbonization transformation, and there is a shortage of specific talent in this area within SMEs.
Kürpick et al. (2024)	7. Unquantified decisions within the Twin Transition complicate long-term decision-making.	Unquantified decisions hamper long-term decision-making. Current reporting and assessment standards are opaque, leading to improvement potential for combined maturity models (CMM).
Kürpick et al. (2024)	9. Resistance from employees may arise due to the extensive changes required by the Twin Transition.	Employee resistance may arise from the radical changes required by the Twin Transition. Industry 4.0 may lead to deregulation of employment relationships, pressure for constant availability and new opportunities to evaluate employee performance digitally. The adoption of digital platforms has been met with mixed opinions, with some pointing to opportunities for social mobility, while others warn of the blurring of boundaries between manual and intellectual work.
Kren and Lawless (2024)	3. The sustainability impact of digital technologies remains poorly understood by manufacturing companies.	The impact of digital technologies on sustainability is poorly understood by manufacturing companies. The article highlights that companies are not yet fully exploiting the potential of digital technologies to help shift to greener production methods.
Kren and Lawless (2024)	6. The evolving nature of the Twin Transition adds complexity to their implementation for manufacturing companies.	The evolving nature of the dual transition makes implementation more complex for manufacturing companies. The article cites uncertainty as a barrier, with companies potentially delaying investments in climate-friendly technologies pending clarity on the evolution of technologies, carbon prices, standards and regulations.

Research paper	Challenge with number	Descriptive summary
Kren and Lawless (2024)	7. Unquantified decisions within the Twin Transition complicate long-term decision-making.	The article suggests that there is a need for policies to incentivize investments in a direction that helps address climate change, suggesting that quantifying the benefits of these investments is important.
Kren and Lawless (2024)	8. The Twin Transition demands new skills from both the company and its employees.	The dual transition requires new skills from both the firm and its employees. The article highlights the need for additional investment in skills in the labor market to fully exploit the new technologies and reap the full productivity benefits, both at the firm and national level.
Kren and Lawless (2024)	12. Navigating the dual and evolving regulations governing the Twin Transition presents an added challenge.	Navigating the dual and evolving regulatory landscape surrounding the dual transition poses an additional challenge. The article notes that companies may delay investments in climate-friendly technologies pending clarity on the evolution of technologies, carbon prices, standards and regulations.
Re et al. (2024)	3. The sustainability impact of digital technologies remains poorly understood by manufacturing companies.	The article indicates that the impact of digital technologies on sustainability is still not sufficiently understood by manufacturing companies. This lack of insight hampers the ability of companies to make informed decisions about the adoption and implementation of digital technologies to promote sustainability.
Re et al. (2024)	10. The Twin Transition may necessitate organizational restructuring, such as increased collaboration.	The paper emphasizes that companies may need to increase collaboration and build innovation networks to navigate the Twin Transition challenges. Choosing an open innovation approach may allow companies to keep pace with market challenges, but SMEs' limited formalization and smaller networks can be a hindrance.
Re et al. (2024)	12. Navigating the dual and evolving regulations governing the Twin Transition presents an added challenge.	The paper highlights that companies face an uncertain landscape where standards and technologies may not be mature or readily accessible.
Chatzistamoulou (2023)	2. There is a lack of understanding in what the economic returns will be when implementing measures for the Twin Transition.	The paper highlights that many manufacturing companies struggle to assess the financial benefits of adopting Twin Transition measures. This uncertainty stems from the long-term nature of returns.
Chatzistamoulou (2023)	3. The sustainability impact of digital technologies remains poorly understood by manufacturing companies.	Manufacturing firms often lack comprehensive assessments of how digitalization affects sustainability. While digital solutions can enhance efficiency, their environmental footprint remains a poorly understood trade-off.
Chatzistamoulou (2023)	4. There is a shortage of clear, practice-based examples of example transition pathways for the Twin Transition.	Companies lack concrete examples of example transition frameworks that successfully integrate digital and green strategies. Without well-documented case studies or best practices, businesses face difficulties in structuring their transformation efforts effectively.
Chatzistamoulou (2023)	6. The evolving nature of the Twin Transition adds complexity to their implementation for manufacturing companies.	The dynamic development of digital and sustainability trends makes implementation challenging. Technologies, regulations, and market demands are continuously shifting, requiring companies to adapt without a stable roadmap.
Chatzistamoulou (2023)	12. Navigating the dual and evolving regulations governing the Twin Transition presents an added challenge.	The coexistence of digital and sustainability policies creates a regulatory challenge. Companies must comply with multiple frameworks that are frequently updated, making it difficult to align strategies without facing compliance risks or additional costs.
Kekkonen et al. (2023)	1. The high implementation costs of both the digital and sustainability aspects of the Twin Transition present a significant barrier.	The financial barriers are a key challenge, as companies often face high investment costs in digital and green technologies. Many businesses perceive the green transition as a costly challenge due to limited access to financing, financial barriers, and increased operational costs.
Kekkonen et al. (2023)	2. There is a lack of understanding in what the economic returns will be when implementing measures for the Twin Transition.	Manufacturers struggle with understanding the economic benefits of Twin Transition, as there is no clear data on long-term returns. The study notes that businesses are unsure whether the transition will result in competitive advantages or simply increase costs.

Research paper	Challenge with number	Descriptive summary
Kekkonen et al. (2023)	3. The sustainability impact of digital technologies remains poorly understood by manufacturing companies.	The impact of digitalization on sustainability is not fully understood by many companies. The research suggests that while digital technologies are seen as necessary, there is limited knowledge about their actual effects on environmental sustainability.
Kekkonen et al. (2023)	6. The evolving nature of the Twin Transition adds complexity to their implementation for manufacturing companies.	The quick development of regulations, technologies, and policies makes implementation complex. Manufacturing companies struggle to keep up with evolving digital and sustainability trends, leading to uncertainty in decision-making.
Kekkonen et al. (2023)	7. Unquantified decisions within the Twin Transition complicate long-term decision-making.	The lack of clear metrics for evaluating the Twin Transition complicates strategic planning. Many businesses lack sufficient data to make informed long-term investment decisions, further hindering the transition.
Tabares et al. (2025)	2. There is a lack of understanding in what the economic returns will be when implementing measures for the Twin Transition.	Lack of insight into economic returns: There is a lack of clarity about the economic benefits of implementing the Twin Transition. This lack of a clear vision of the economic benefits can reduce the willingness to invest.
Tabares et al. (2025)	6. The evolving nature of the Twin Transition adds complexity to their implementation for manufacturing companies.	The continuous development of the Twin Transition makes the implementation more complex for manufacturing companies. The dynamic external environment, including technological developments and changing customer needs, complicates the implementation of the Twin Transition.
Tabares et al. (2025)	7. Unquantified decisions within the Twin Transition complicate long-term decision-making.	Unmeasurable decisions within the Twin Transition complicate long-term decision-making.
Tabares et al. (2025)	8. The Twin Transition demands new skills from both the company and its employees.	The Twin Transition require new skills from both the company and the employees. This includes developing digital skills, knowledge of green technologies and internal organizational management skills.
Tabares et al. (2025)	10. The Twin Transition may necessitate organizational restructuring, such as increased collaboration.	The Twin Transition may require a reorganization of the organization, such as an increase in collaboration. Successful implementation requires a shift in organizational structure and an increase in collaboration between different departments.
Tabares et al. (2025)	12. Navigating the dual and evolving regulations governing the Twin Transition presents an added challenge.	Navigating the dual and evolving regulations related to the Twin Transition poses an additional challenge. Companies need to stay up to date with the changing laws and regulations around sustainability and digital transformation.
Breiter et al. (2024)	1. The high implementation costs of both the digital and sustainability aspects of the Twin Transition present a significant barrier.	The paper acknowledges the resource constraints that organizations face when pursuing Twin Transformation. The research notes that not every organization might have sufficient financial resources to implement all capabilities needed for the Twin Transformation.
Breiter et al. (2024)	6. The evolving nature of the Twin Transition adds complexity to their implementation for manufacturing companies.	The authors note that mastering Twin Transformation is not trivial and requires integrated dynamic capabilities that must be continuously developed, sustained, and monitored. They emphasize that Twin Transformation affects all organizational layers both internally and externally.
Breiter et al. (2024)	8. The Twin Transition demands new skills from both the company and its employees.	The paper states that organizations need dynamic capabilities to change their existing business practices to address rapidly changing environments.
Findik et al. (2023)	6. The evolving nature of the Twin Transition adds complexity to their implementation for manufacturing companies.	The paper highlights that the evolving nature of the Twin Transition introduces complexity for manufacturers, particularly SMEs. Since Industry 4.0 technologies are continuously advancing, companies must adapt to new developments while also restructuring their operations for circular economy practices. This dual shift requires firms to redesign supply chains, integrate advanced digital tools, and manage new data flows, all while keeping up with shifting regulations and technological innovations.

Research paper	Challenge with number	Descriptive summary
Findik et al. (2023)	7. Unquantified decisions within the Twin Transition complicate long-term decision-making.	The paper notes that firms struggle with informational problems, particularly in recycling and reusing materials due to a lack of data on material flows. While Industry 4.0 technologies can provide data-driven insights, the financial burden and uncertainty surrounding their implementation prevent companies from fully leveraging them. Without clear metrics on return on investment, firms hesitate to make large-scale, long-term commitments to the Twin Transition.
Findik et al. (2023)	9. Resistance from employees may arise due to the extensive changes required by the Twin Transition.	The paper mentions that companies face challenges in adopting digital and circular practices due to a lack of technical skills and environmental culture. Employees may resist these changes because of fears of job displacement, the need for retraining, or uncertainty about new technologies.
Diodato et al. (2023)	4. There is a shortage of clear, practice-based examples of example transition pathways for the Twin Transition.	The paper suggests that more research is needed into the specific typologies of digital bundling that firms select and their impact on eco-innovation.
Diodato et al. (2023)	8. The Twin Transition demands new skills from both the company and its employees.	The paper states that digital transformation is driving demand for workers with high-quality training and technical knowledge. There are concerns that robotization will replace labor in routine tasks, potentially leading to technological unemployment.
Fouquet and Hippe (2022)	1. The high implementation costs of both the digital and sustainability aspects of the Twin Transition present a significant barrier.	The Twin Transition requires significant investments in both digital technologies and sustainable practices. The costs of implementing new digital systems and switching to sustainable energy sources can be significant, which can be a major barrier.
Fouquet and Hippe (2022)	2. There is a lack of understanding in what the economic returns will be when implementing measures for the Twin Transition.	It is often unclear what the concrete economic benefits of investing in the Twin Transition will be. This lack of certainty about the return on investment can make companies reluctant to invest in this transition, especially if the benefits are not immediately demonstrable in the short term.
Fouquet and Hippe (2022)	7. Unquantified decisions within the Twin Transition complicate long-term decision-making.	Many decisions within the Twin Transition are complex and difficult to quantify. This uncertainty makes it difficult to make strategic decisions and to map out a clear roadmap for the future.
Fouquet and Hippe (2022)	8. The Twin Transition demands new skills from both the company and its employees.	The Twin Transition requires companies and their employees to develop new skills.
Sassanelli et al. (2024)	7. Unquantified decisions within the Twin Transition complicate long-term decision-making.	The article argues that sustainability is a balance between the three dimensions of economy, environment and society, where production processes are developed to meet the needs of consumers, but also the interests of investors. There is not always convergence between shareholders and stakeholders, so there is a need for a pragmatic sustainable and digital model can identify a local optimum that leads to rational use of resources.
Sassanelli et al. (2024)	8. The Twin Transition demands new skills from both the company and its employees.	Tackling certification and making systems integrated and interoperable increasingly requires new types of managers, workers, operators and employees with increasingly heterogeneous skills and competences (not only technical and environmental, but also digital, resilient and soft).
Benedetto and Forleo (2024)	3. The sustainability impact of digital technologies remains poorly understood by manufacturing companies.	The paper discusses that impact of digital technologies on sustainability remains unclear to many manufacturers. This is partly because separate research traditions have historically examined digitalization and sustainability, and only recently have efforts emerged to integrate them into a unified "Twin Transition" approach. The lack of a well-established framework linking digital tools to sustainability benefits means that firms may struggle to evaluate how these technologies contribute to resource efficiency, waste reduction, and environmental protection.

Research paper	Challenge with number	Descriptive summary
Benedetto and Forleo (2024)	9. Resistance from employees may arise due to the extensive changes required by the Twin Transition.	The study highlights that the transition to digital and sustainable practices requires significant changes at multiple levels, including governance, operational processes, and stakeholder coordination. Employees may resist these changes due to unfamiliarity with new digital tools, concerns about job security, or difficulty adapting to new workflows.
Elyasi et al. (2024)	1. The high implementation costs of both the digital and sustainability aspects of the Twin Transition present a significant barrier.	The paper acknowledges that integrating especially AI in manufacturing requires substantial investment, particularly in transitioning from traditional processes to AI-driven systems. The financial burden of adopting AI-based solutions aligns with the broader challenge of high costs associated with both digital and sustainable transitions.
Elyasi et al. (2024)	2. There is a lack of understanding in what the economic returns will be when implementing measures for the Twin Transition.	The paper highlights that while AI promises increased operational efficiency, adaptability, and sustainability, manufacturers often struggle to predict the financial returns of these investments. This uncertainty can deter companies from fully embracing AI solutions, mirroring the broader hesitation regarding the Twin Transition due to unclear economic outcomes.
Elyasi et al. (2024)	3. The sustainability impact of digital technologies remains poorly understood by manufacturing companies.	The study emphasizes the need for an integrated approach that considers economic, environmental, and societal sustainability. While AI can optimize resource utilization and promote second-hand equipment usage, manufacturing companies still lack a clear understanding of its overall sustainability footprint.
Christmann et al. (2024)	8. The Twin Transition demands new skills from both the company and its employees.	Many organizations lack the knowledge and guidance needed to develop essential Twin Transformation capabilities. Twin transformation is a multi- and interdisciplinary construct that is not only the responsibility of and driven by top management but also requires the collaboration of all departments within the organization.
Christmann et al. (2024)	9. Resistance from employees may arise due to the extensive changes required by the Twin Transition.	Employee resistance may arise due to the extensive changes that Twin Transformation requires. Digital transformation promotes continuous change and creates tensions between the "old" and the "new". Sustainability transformation can help motivate employees to support transformational activities.
Christmann et al. (2024)	11. There is insufficient focus on social sustainability within the Twin Transition, as the link between environmental sustainability and digitalization is clearer.	When using digitalization and sustainability simultaneously, one transformation is prioritized over the other, or sustainability is reduced to ecological aspects instead of integrating the holistic approach (ecological, social and economic progress).
Fu and Xu (2024)	1. The high implementation costs of both the digital and sustainability aspects of the Twin Transition present a significant barrier.	The paper highlights that while digitalization promotes green innovation, it also presents financial challenges, particularly for SMEs. The cost of adopting emerging digital technologies like cloud computing, artificial intelligence, and smart monitoring systems can be prohibitive. Furthermore, the study notes that financing constraints are a key barrier to enterprise green innovation, with digital technology only partially alleviating these constraints for SMEs. This indicates that despite the potential benefits of digitalization for sustainability, high upfront costs hinder widespread adoption, aligning with the concern that the Twin Transition require significant investment.
Fu and Xu (2024)	7. Unquantified decisions within the Twin Transition complicate long-term decision-making.	The lack of clear definitions and example measures of digital transformation leads to uncertainty in decision-making.
Benedetti et al. (2023)	1. The high implementation costs of both the digital and sustainability aspects of the Twin Transition present a significant barrier.	The paper highlights that the costs associated with digital transformation and energy efficiency improvements can be a significant barrier. Digitalization requires investments in new technologies, infrastructure, and skills, while the sustainability aspect often demands additional investments in energy-efficient equipment and renewable energy sources. Both transformations are expensive, and manufacturers might face difficulties in allocating the necessary financial resources for such large-scale changes. The complexity of integrating both digital and sustainability efforts compounds the costs, making it challenging for firms to afford simultaneous transformations.

Research paper	Challenge with number	Descriptive summary
Benedetti et al. (2023)	4. There is a shortage of clear, practice-based examples of example transition pathways for the Twin Transition.	The paper points out that clear, practical examples of example transition pathways are lacking. While the European Union is moving toward a Twin Transition strategy through frameworks like the Digital Economy and Society Index (DESI), the lack of well-documented, sector-specific best practices creates uncertainty. This absence of clear examples makes it harder for manufacturing companies to visualize how to implement these transformations in a structured, efficient way.
Benedetti et al. (2023)	6. The evolving nature of the Twin Transition adds complexity to their implementation for manufacturing companies.	The paper also emphasizes that the evolving nature of the Twin Transition adds further complexity. As digital technologies and sustainability goals rapidly change, manufacturing companies must constantly adapt their strategies.
Kirov (2023)	4. There is a shortage of clear, practice-based examples of example transition pathways for the Twin Transition.	Companies lack models to follow, with only some large multinational subsidiaries having sustainability objectives, and these are primarily to comply with headquarters' requirements.
Kirov (2023)	6. The evolving nature of the Twin Transition adds complexity to their implementation for manufacturing companies.	The paper mentions that even when environmental benefits occur (like during pandemic remote work), these are "unintended consequence from other policies" rather than strategic integration, so changes in the Twin Transition do not result in new strategic integration.
Kirov (2023)	8. The Twin Transition demands new skills from both the company and its employees.	The digital transformation created significant employment opportunities, but the paper suggests companies lack the capabilities to integrate sustainability practices.
Kirov (2023)	11. There is insufficient focus on social sustainability within the Twin Transition, as the link between environmental sustainability and digitalization is clearer.	The paper highlights the disconnect between decent work conditions and environmental sustainability.
Sareen et al. (2023)	9. Resistance from employees may arise due to the extensive changes required by the Twin Transition.	The paper suggests that the Twin Transition require significant changes throughout organizations, which naturally leads to employee resistance. This resistance stems from uncertainty about job security as digitalization may lead to automation of certain tasks and the need for employees to adapt to new digital tools and sustainability practices simultaneously.
Sareen et al. (2023)	10. The Twin Transition may necessitate organizational restructuring, such as increased collaboration.	The Twin Transition require breaking down of traditional siloed departments to enable cross-functional teams focused on both digital transformation and sustainability goals. There is also the need to balance "commoning" (collaborative, open approaches) versus "enclosure" (proprietary, restricted approaches) in organizational structures.
Sareen et al. (2023)	11. There is insufficient focus on social sustainability within the Twin Transition, as the link between environmental sustainability and digitalization is clearer.	The findings suggest that current implementation approaches show "tendencies of enclosure and missed opportunities to achieve commoning of energy infrastructure for public benefit," indicating that social sustainability considerations are being inadequately addressed.
Peças et al. (2023)	3. The sustainability impact of digital technologies remains poorly understood by manufacturing companies.	The paper specifically mentions the integration of data-driven approaches with sustainability assessment as "one of the most relevant challenges" in the Twin Transition.
Peças et al. (2023)	7. Unquantified decisions within the Twin Transition complicate long-term decision-making.	The paper strongly emphasizes the importance of quantitative metrics and indicators. The authors specifically highlight that some published approaches are lacking "quantitative data (KPI) as well as indicators' weights and interrelations."
Rahnama et al. (2022)	2. There is a lack of understanding in what the economic returns will be when implementing measures for the Twin Transition.	The paper notes that sustainability requirements from customers are "often vague or not explicitly paid for." This creates uncertainty about economic returns for technology solution providers. There's an explicit mention that manufacturing customers are mostly interested in the financial perspective while investing in production solutions.

Research paper	Challenge with number	Descriptive summary
Ortega-Gras et al. (2021)	1. The high implementation costs of both the digital and sustainability aspects of the Twin Transition present a significant barrier.	The technologies that drive both Industry 4.0 and the sustainability transition require significant investment. The paper specifically notes that these technologies involve "rapid innovation cycles" and "high capital expenditure," creating financial barriers that can impede adoption.
Ortega-Gras et al. (2021)	3. The sustainability impact of digital technologies remains poorly understood by manufacturing companies.	The paper states there is not enough knowledge and practical examples on what the impacts are of key technologies for the Twin Transition in manufacturing.
Ortega-Gras et al. (2021)	4. There is a shortage of clear, practice-based examples of example transition pathways for the Twin Transition.	The paper mentions that there are too little real use cases to inspire manufacturers to implement the Twin Transition.
Ortega-Gras et al. (2021)	8. The Twin Transition demands new skills from both the company and its employees.	The paper states that most manufacturers are not prepared for the Twin Transition and therefore they should launch new initiatives to ensure that employees have the necessary skills. The paper emphasizes that there could be training synergies for the Twin Transition.

B.1.4. Thirteen synthesized Twin Transition challenges

Challenge 1: The high implementation costs of both the digital and sustainability aspects of the Twin Transition present a significant barrier.

Digital transformation requires investments in new technologies, infrastructure, and workforce skills, while sustainability efforts demand spending on energy-efficient equipment and renewable energy sources (Benedetti et al., 2023).

Adopting new digital technologies entails substantial financial commitments, not only for initial investments but also for implementation, operation, and maintenance (Sjödin et al., 2024; Stucki et al., 2024; Gulbrandsen-Dahl et al., 2024)). Transitioning to digital systems and sustainable energy sources is particularly costly, creating a major barrier to adoption (Fouquet and Hippe, 2022). Integrating AI into manufacturing, for example, requires significant investment, especially when shifting from traditional processes to AI-driven systems (Elyasi et al., 2024). Additionally, rapid innovation cycles and high capital expenditures make implementation even more challenging (Ortega-Gras et al., 2021).

Financial constraints are a key barrier, particularly for manufacturers with limited resources (Breiter et al., 2024). Many businesses perceive the green transition as financially burdensome due to increased operational costs (Kekkonen et al., 2023). Moreover, funding limitations hinder enterprise green innovation, and digital technology only partially mitigates these constraints (Fu and Xu, 2024).

The complexity of integrating both transformations further compounds financial pressures, making it difficult for firms to afford simultaneous changes (Benedetti et al., 2023). The dual investment in digital transformation and sustainability can strain financial resources, leading to delays in implementation (Chen et al., 2023).

Challenge 2: There is a lack of understanding in what the economic returns will be when implementing measures for the Twin Transition.

A lack of clarity around the economic benefits of digital transformation often makes companies hesitant to invest in digital technologies (Gulbrandsen-Dahl et al., 2024; Rahnama et al., 2022). This uncertainty arises from the long-term nature of returns (Chatzistamoulou, 2023) and is further compounded by the immaturity of certain technologies and a limited understanding of their actual benefits (Chatzistamoulou, 2023).

Manufacturers struggle to align economic and environmental objectives with technological needs (Spaltini et al., 2024a). Quantifying the return on investment for digital and sustainable technologies is particularly challenging, making decision-making riskier (Stucki et al., 2024). Many companies also lack transparency regarding the economic impact of sustainability initiatives (Spaltini et al., 2024b; Elyasi et al., 2024). As a result, they are unsure whether these transitions will provide competitive advantages or merely increase costs (Kekkonen et al., 2023).

This uncertainty makes it difficult for businesses to justify investments and make informed decisions, especially when the benefits are not immediately apparent in the short term (Spaltini et al., 2024b; Tabares et al., 2025; Fouquet and Hippe, 2022).

Challenge 3: The sustainability impact of digital technologies remains poorly understood by manufacturing companies.

Manufacturing companies often struggle to assess whether digital technologies support or hinder sustainability goals (Stucki et al., 2024; Kren and Lawless, 2024). While digital solutions can improve efficiency, their environmental footprint remains a poorly understood trade-off (Chatzistamoulou, 2023; Kekkonen et al., 2023; Elyasi et al., 2024). On a macroeconomic scale, the impact of digital transformation on energy consumption depends on factors such as sector growth, energy efficiency improvements, economic trends, and structural shifts within industries (Kürpick et al., 2024).

One key challenge is the historical separation of research on digital transformation and sustainability, with only recent efforts attempting to integrate them into a unified "Twin Transition" approach (Benedetto and Forleo, 2024). Additionally, there is a lack of practical examples illustrating the real-world impacts of key Twin Transition technologies in manufacturing (Ortega-Gras et al., 2021). The integration of data-driven approaches with sustainability assessments remains "one of the most relevant challenges" in achieving this transition (Peças et al., 2023).

Manufacturing companies also lack structured models to effectively merge Industry 4.0 with circular economy principles (Spaltini et al., 2024a). This makes it difficult to select and implement the right technologies to support the transition (Spaltini et al., 2024b). As a result, this knowledge gap slows adoption and prevents manufacturers from fully realizing the sustainability benefits of digital transformation (Spaltini et al., 2024a).

Challenge 4: There is a shortage of clear, practice-based examples of transition pathways for the Twin Transition.

While the European Union is advancing a Twin Transition strategy through frameworks like the Digital Economy and Society Index (DESI), the lack of well-documented, sector-specific best practices creates uncertainty (Benedetti et al., 2023). Companies seeking to make this transformation often struggle with how to implement it in practical terms (Trevisan et al., 2024). The absence of concrete examples makes it difficult to choose the right strategies and technologies and to determine the necessary investments (Trevisan et al., 2024; Chatzistamoulou, 2023; Diodato et al., 2023). Without clear guidance, companies also face challenges in benchmarking their progress and adopting best practices (Chen et al., 2023).

A significant issue is the lack of structured models for businesses to follow. Only some large multinational subsidiaries have defined sustainability objectives, and these are primarily driven by headquarters' compliance requirements (Kirov, 2023). Additionally, there is a shortage of well-documented, practice-based examples showing how companies can successfully navigate the Twin Transition (Chen et al., 2023; Perossa et al., 2023). The limited availability of real-world use cases makes it difficult for manufacturers to find inspiration and concrete direction for implementation (Ortega-Gras et al., 2021).

Challenge 5: Manufacturing companies lack tailored strategies that address their unique starting points in each of the Twin Transition.

Companies struggle to balance short- and long-term goals when implementing Twin Transition strategies (Spaltini et al., 2024a). Many strategies fail due to misalignment between digital transformation and sustainability, as well as the absence of methodologies that address the specific needs of different manufacturers (Spaltini et al., 2024a; Kürpick et al., 2023, 2024). A key challenge is that current assessment tools are too generic and do not account for a company's size, production type, or unique characteristics (Abilakimova et al., 2025).

Challenge 6: The evolving nature of the Twin Transition adds complexity to their implementation for manufacturing companies.

The Twin Transition involve constantly evolving domains: in the digital transition, new technologies are continuously developed and introduced, while in the sustainability transition, new impacts emerge across supply chains (Abilakimova et al., 2025; Trevisan et al., 2024; Chatzistamoulou, 2023). This dynamic external environment, including technological advancements and shifting customer needs, complicates implementation (Tabares et al., 2025; Findik et al., 2023; Benedetti et al., 2023).

Uncertainty surrounding technological evolution and market conditions often leads companies to delay the adoption of new digital and sustainable solutions (Kren and Lawless, 2024). Even when environmental benefits do occur, such as reduced emissions from remote work during the pandemic, these are typically "unintended consequences from other policies" rather than the result of strategic integration (Kirov, 2023).

To navigate these challenges, companies must develop dynamic capabilities that allow them to adapt to new technologies and changing market conditions (Sjödin et al., 2024). These capabilities must be continuously developed, sustained, and monitored to ensure long-term success (Breiter et al., 2024). This requires not only investments in technology but also in organizational agility and rapid responsiveness (Sjödin et al., 2024; Kürpick et al., 2023). However, without structured guidance, manufacturers struggle to keep pace with the rapid evolution of both digital and sustainability transitions (Spaltini et al., 2024a; Chen et al., 2023; Kekkonen et al., 2023).

Challenge 7: Unquantified decisions within the Twin Transition complicate long-term decision-making.

A major challenge in the Twin Transition is the lack of quantification in decision-making, which complicates long-term strategic planning (Kürpick et al., 2024; Tabares et al., 2025; Fouquet and Hippe, 2022). Current reporting and assessment standards are opaque, making it difficult for manufacturers to evaluate their progress (Kürpick et al., 2023; Kren and Lawless, 2024). As a result, many struggle to measure their performance in digital and green initiatives (Abilakimova et al., 2025).

Clear, quantitative metrics and indicators are essential to reducing uncertainty in decision-making (Peças et al., 2023). However, the lack of standardized evaluation criteria makes it difficult for manufacturing companies to quantify Twin Transition decisions and, as a result, to develop effective strategies (Kekkonen et al., 2023; Sassanelli et al., 2024; Fu and Xu, 2024). Without sufficient data, many firms struggle to make informed long-term investment decisions, further delaying progress in the Twin Transition (Del Vecchio et al., 2025; Kekkonen et al., 2023).

Challenge 8: The Twin Transition demands new skills from both the company and its employees.

The Twin Transition demands new skills from both companies and their employees (Trevisan et al., 2024). These include expertise in digital technologies, resilience, green technologies, and internal organizational management (Trevisan et al., 2024; Tabares et al., 2025). Employees must learn to work with new software and machinery while also developing the ability to analyze and interpret data (Trevisan et al., 2024; Kirov, 2023).

At an organizational level, companies need dynamic capabilities to adapt their business practices in response to rapidly changing environments (Breiter et al., 2024; Sassanelli et al., 2024). The Twin Transition is inherently multi- and interdisciplinary, requiring collaboration across all departments rather than being solely the responsibility of top management (Christmann et al., 2024).

However, a lack of knowledge or competence in developing, implementing, or using digital technologies can significantly hinder digital transformation efforts and prevent organizations from fully utilizing new solutions (Gulbrandsen-Dahl et al., 2024). Similarly, insufficient expertise in sustainability or digital transformation may slow progress, often necessitating the involvement of external experts (Kürpick et al., 2023). To fully exploit new technologies and maximize productivity gains, additional investment in workforce skills is essential (Kren and Lawless, 2024; Diodato et al., 2023; Fu and Xu, 2024). There may also be opportunities to create training synergies between the Twin Transition (Ortega-Gras et al., 2021).

Challenge 9: Resistance from employees may arise due to the extensive changes required by the Twin Transition.

Digital transformation drives continuous change and creates tensions between the "old" and the "new" (Christmann et al., 2024). Industry 4.0 may lead to deregulation of employment relationships, pressure for constant availability, and new ways of evaluating employee performance (Kürpick et al., 2023). The adoption of digital platforms has sparked mixed reactions, with some seeing opportunities for social mobility, while others warn of the blurring of boundaries between manual and intellectual work (Kürpick et al., 2023).

Employees often resist these changes due to fears of the need for retraining, or unfamiliarity with new digital tools (Findik et al., 2023; Benedetto and Forleo, 2024). This resistance is further fueled by concerns about job security as digital transformation may automate certain tasks and require employees to adapt to both new technologies and sustainability practices simultaneously (Sareen et al., 2023).

Resistance can emerge at all levels of a company (Gulbrandsen-Dahl et al., 2024; Kürpick et al., 2024), often manifesting as an overemphasis on the negative aspects of technology, which can lead to

rejection of the business case (Gulbrandsen-Dahl et al., 2024). However, sustainability transformation can motivate employees to support the simultaneous Twin Transition (Christmann et al., 2024).

Challenge 10: The Twin Transition may necessitate organizational restructuring, such as increased collaboration.

A successful Twin Transition requires a shift in how companies view their role in the value chain and how they create value (Sjödin et al., 2024; Stucki et al., 2024). This involves fundamental changes in thinking about industrial processes, supply chain management, and service delivery (Abilakimova et al., 2025). Companies must integrate technological and managerial transformations while ensuring cross-functional collaboration (Spaltini et al., 2024a).

Collaboration, both within organizations and with supply chain partners, is critical for success (Abilakimova et al., 2025). This can be a challenge for companies that traditionally operate in silos or lack experience in strategic partnerships (Sjödin et al., 2024). Implementing the Twin Transition often requires different departments to work more closely together, which may result in changes to organizational structures and new roles for employees (Trevisan et al., 2024; Tabares et al., 2025).

To keep pace with market challenges, adopting an open innovation approach can help manufacturing companies (Re et al., 2024). However, this also requires balancing collaborative, open approaches ("commoning") with proprietary, restricted ones ("enclosure") in organizational structures.

Challenge 11: There is insufficient focus on social sustainability within the Twin Transition, as the link between environmental sustainability and digitalization is clearer.

Companies often prioritize economic and environmental sustainability over social sustainability, especially when digital transformation drives sustainability efforts (Abilakimova et al., 2025). This can lead to a disconnect between decent work conditions and environmental sustainability (Kirov, 2023). When digital transformation and sustainability are pursued simultaneously, one transformation is typically prioritized over the other, or sustainability is reduced to ecological aspects, rather than integrating a holistic approach that includes ecological, social, and economic progress (Christmann et al., 2024).

The complexity of the Twin Transition requires expertise in technology (both digital and green), as well as management and social considerations (Del Vecchio et al., 2025). This means in practice that especially social sustainability remains inadequately addressed in many cases (Sareen et al., 2023).

Challenge 12: Navigating the dual and evolving regulations governing the Twin Transition presents an added challenge.

Companies must stay on top of frequently updated regulations to ensure compliance (Spaltini et al., 2024b). However, regulatory frameworks are often still in development, creating uncertainty around requirements and enforcement (Re et al., 2024). The unpredictability of regulations, including shifting carbon pricing, sustainability standards, and compliance rules, makes it difficult for companies to align their strategies without facing compliance risks or incurring additional costs (Chatzistamoulou, 2023; Tabares et al., 2025). As a result, many manufacturers hesitate to invest in climate-friendly technologies, waiting for clearer regulatory guidance before committing to long-term initiatives (Kren and Lawless, 2024).

Challenge 13: Managing regulations related to the Twin Transition domain while remaining competitive is difficult.

Manufacturing companies face pressure to meet environmental demands while staying competitive (Abilakimova et al., 2025; Sjödin et al., 2024). Striking a balance between complying with regulations related to the Twin Transition and maintaining a competitive advantage is a significant challenge (Spaltini et al., 2024b). Managing these regulatory requirements while staying competitive is difficult for many companies.

B.2. Interviews

B.2.1. Survey questions

This survey will serve as the basis for our interview conversation. It should take no more than five minutes to complete. Your responses will help tailor the discussion to the most relevant topics.

Goal of this survey and the interview: to specify the literature findings on the simultaneous Twin Transition implementation challenges for the manufacturing sector in general to challenges that are relevant to the Dutch high-tech manufacturing sector.

Definition of the Twin Transition in this study: The Twin Transition refers to the simultaneous shift towards sustainability (environmental, social and economic) and digitalization.

Definition of the high-tech sector in this study: High-tech manufacturing is a subset of the manufacturing industry that focuses on producing advanced technological products using innovative techniques, processes, and materials. The high-tech sector comprises sub sectors such as semi-conductor, nanotechnology, advanced materials and medical devices production.

Scope of the study:

- Geographical: only high-tech manufacturing companies in the Netherlands are considered.
- Company size: LEs (non-SME, > 500 employees, >50 million turnover)
- Process boundaries: company-level, only the processes with the high-tech manufacturer site are considered (not inter-company, but only intra-company processes)

Please fill in your full name.

What is your current role/job title? Please fill in all relevant roles.

How would you rate your knowledge of digitalization in the Dutch high-tech manufacturing sector?

- Slightly knowledgeable
- Moderately knowledgeable
- Very knowledgeable
- Extremely knowledgeable

How would you rate your knowledge of sustainability in the Dutch high-tech manufacturing sector?

- Slightly knowledgeable
- Moderately knowledgeable
- Very knowledgeable
- Extremely knowledgeable

Thirteen challenges related to implementing the Twin Transition in the manufacturing sector have been identified through a structured literature review. In the interview, we will refine these challenges specifically for the Dutch high-tech manufacturing sector. Based on your ranking of their relevance in both the short and long term, we will select and discuss key challenges during the interview.

Please rank the following challenges based on their perceived relevance to the Dutch high-tech manufacturing sector over the next 5 years, according to your professional perspective. (1st is most relevant, 13th is least relevant)

1. The high implementation costs of both the digital and sustainability aspects of the Twin Transition present a significant barrier.
2. There is a lack of understanding in what the economic returns will be when implementing measures for the Twin Transition.
3. The sustainability impact of digital technologies remains poorly understood by manufacturing companies.
4. There is a shortage of clear, practice-based examples of transition pathways for the Twin Transition.
5. Manufacturing companies lack tailored strategies that address their unique starting points in the Twin Transition.

6. The evolving nature of the Twin Transition adds complexity to their implementation for manufacturing companies.
7. Unquantified decisions within the Twin Transition complicate long-term decision-making.
8. The Twin Transition demands new skills from both the company and its employees.
9. Resistance from employees may arise due to the extensive changes required by the Twin Transition.
10. The Twin Transition may necessitate organizational restructuring, such as increased collaboration.
11. There is insufficient focus on social sustainability within the Twin Transition, as the link between environmental sustainability and digitalization is clearer.
12. Navigating the dual and evolving regulations governing the Twin Transition presents an added challenge.
13. Managing regulations related to the Twin Transition domains while remaining competitive is difficult.

Please rank the following challenges based on their perceived relevance to the Dutch high-tech manufacturing sector over the next 5–10 years, according to your professional perspective. (1st is most relevant, 13th is least relevant)

1. The high implementation costs of both the digital and sustainability aspects of the Twin Transition present a significant barrier.
2. There is a lack of understanding in what the economic returns will be when implementing measures for the Twin Transition.
3. The sustainability impact of digital technologies remains poorly understood by manufacturing companies.
4. There is a shortage of clear, practice-based examples of transition pathways for the Twin Transition.
5. Manufacturing companies lack tailored strategies that address their unique starting points in each of the Twin Transition parts.
6. The evolving nature of the Twin Transition adds complexity to their implementation for manufacturing companies.
7. Unquantified decisions within the Twin Transition complicate long-term decision-making.
8. The Twin Transition demands new skills from both the company and its employees.
9. Resistance from employees may arise due to the extensive changes required by the Twin Transition.
10. The Twin Transition may necessitate organizational restructuring, such as increased collaboration.
11. There is insufficient focus on social sustainability within the Twin Transition, as the link between environmental sustainability and digitalization is clearer.
12. Navigating the dual and evolving regulations governing the Twin Transition presents an added challenge.
13. Managing regulations related to the Twin Transition domains while remaining competitive is difficult.

We thank you for your time spent taking this survey. Your response has been recorded.

B.2.2. Interview protocol

Begin with an introduction of myself and the research. Explain that the goal is to specify the literature-based challenges in implementing the Twin Transition for Dutch high-tech manufacturing companies. Emphasize that the interviewee's experiences will be valuable. Ask if the interviewee has any questions about the consent form. Repeat the consent elements previously shown to the interviewee during the before provided and signed consent-form. Ask for a brief introduction of the interviewee. Verify the name and current role of the interviewee.

1. Starting questions

These initial questions aim to provide context and gather the interviewee's perspective:

1. *Can you briefly describe your role and experience in/with the Dutch high-tech manufacturing sector?*
2. *How would you describe the state of digital and sustainability transitions in Dutch high-tech manufacturing? Do you see them as interlinked or separate in the Dutch high-tech manufacturing sector?*
3. *What major shifts have you observed regarding digitalization and sustainability in this sector?*

2. Challenge specific questions

(Start with highest ranking, see how much time is left for questions with lower ranking)

Challenge 1: The high implementation costs of both the digital and sustainability aspects of the Twin Transition present a significant barrier.

- *How do Dutch high-tech manufacturing companies perceive the cost burden of implementing digital and sustainability initiatives?*
- *Are there specific cost-related barriers unique to the Dutch context (e.g., energy prices, labor costs, tax structures)?*

Challenge 2: There is a lack of understanding in what the economic returns will be when implementing measures for the Twin Transition.

- *What concerns do Dutch high-tech manufacturers have regarding the return on investment for Twin Transition initiatives?*
- *Which aspects of the Twin Transition have shown clearer economic returns for Dutch high-tech manufacturing companies? Which ones are more unclear?*

Challenge 3: The sustainability impact of digital technologies remains poorly understood by manufacturing companies.

- *Do Dutch high-tech manufacturers assess the environmental impact of digital initiatives? If so, how?*
- *For which aspects of the digital transitions do you think there are clear links of impacts with the sustainability transition for Dutch high-tech manufacturing companies?*

Challenge 4: There is a shortage of clear, practice-based examples of transition pathways for the Twin Transition.

- *How do Dutch high-tech manufacturers currently approach strategy development for the Twin Transition?*
- *What examples or best practices are currently available in the Dutch high-tech manufacturing sector, and why might they be insufficient?*

Challenge 5: Manufacturing companies lack tailored strategies that address their unique starting points in the Twin Transition.

- *What unique aspects of Dutch high-tech manufacturing make it difficult to apply example transition models/roadmaps?*
- *What factors make it difficult for Dutch high-tech manufacturers to develop transition strategies suited to their unique needs?*

Challenge 6: Evolving nature of the transitions

- *Which recent developments (technological, regulatory, market-related) have had the biggest impact on Dutch high-tech manufacturers?*

Challenge 7: Unquantified decisions within the Twin Transition complicate long-term decision-making.

- *What types of Twin Transition decisions are particularly difficult to quantify in the Dutch high-tech manufacturing context?*

- *For practitioners only: How does your company approach decision-making when quantitative data is limited?*

Challenge 8: The Twin Transition demands new skills from both the company and its employees.

- *What are the most important skill gaps Dutch high-tech manufacturers face when implementing the Twin Transition?*
- *How are Dutch high-tech manufacturing companies addressing workforce upskilling or recruitment for digital and sustainability expertise?*

Challenge 9: Resistance from employees may arise due to the extensive changes required by the Twin Transition.

- *What specific aspects of the Twin Transition face the most resistance from employees in Dutch high-tech manufacturing?*
- *What are the main concerns or objections raised by employees in the Dutch high-tech manufacturing sector during implementation of the Twin Transition?*

Challenge 10: The Twin Transition may necessitate organizational restructuring, such as increased collaboration.

- *How do the Twin Transition affect collaboration across departments in Dutch high-tech manufacturing companies?*
- *Are Dutch high-tech manufacturers restructuring their business models or leadership structures in response to these changes?*
- *How has the need for increased collaboration and other organizational changes impacted the Dutch high-tech manufacturing sector?*

Challenge 11: There is insufficient focus on social sustainability within the Twin Transition, as the link between environmental sustainability and digitalization is clearer.

- *How do Dutch high-tech manufacturers perceive the role of social sustainability within the Twin Transition?*
- *Are there examples of Dutch high-tech manufacturing companies successfully integrating social sustainability alongside digitalization and environmental sustainability?*

Challenge 12: Navigating the dual and evolving regulations governing the Twin Transition presents an added challenge.

- *Which regulation is the most relevant for implementing the Twin Transition for Dutch high-tech manufacturers?*
- *What are the most complex regulatory challenges Dutch manufacturers face regarding the Twin Transition?*

Challenge 13: Managing regulations related to the Twin Transition domains while remaining competitive is difficult.

- *Which regulation poses a financial barrier for Dutch high-tech manufacturing companies in implementing the Twin Transition?*
- *How do Dutch high-tech manufacturers manage the balance between regulatory compliance and maintaining global competitiveness?*

3. Closing questions

1. *Are there any challenges you've encountered that are not listed here, but you think are significant for the sector?*
2. *Is there anything you would still like to mention about what we have discussed today?*

B.2.3. Interview summaries

Summary interviewee A1

The complexity of tailoring transition strategies

A1 emphasizes that a one-size-fits-all strategy is insufficient due to the unique nature of high-tech manufacturing. These companies deal with long equipment lifespans, critical raw materials, and complex maintenance needs, all of which shape their transition pathways. A1 pointed out that strategies for implementing repair, reuse, and traceability are highly specific. According to A1, companies also need to coordinate across the value chain. "Sustainability requires collaboration," they explained, "not just with suppliers but with the entire value chain. Everyone needs to benefit."

High costs are not the problem, lack of visibility is

While the cost of implementing new systems is a barrier, A1 clarifies that it's "not that they cannot afford the cost," especially for large firms. The real challenge lies in making both costs and returns visible. Smaller suppliers often struggle more due to limited budgets, but the core issue remains the same: "It's about making things visible, how much cost you have to spend, but also what returns you can expect." A1 also highlighted that digital investments are easier to justify because they are more tangible, whereas the benefits of sustainability are harder to quantify. Companies "embrace technology more... it feels more concrete."

Difficulty quantifying sustainability impacts

A key challenge for firms is identifying relevant sustainability indicators. A1 noted that while it's technically possible to track sustainability metrics through tools like process mining, companies often "don't know what they should quantify." They struggle especially with environmental KPIs related to internal processes rather than materials. "They're not on top of that," A1 added, pointing to a lack of detailed, accessible performance indicators for emissions or water use.

Absence of concrete, transferable best practices

Despite some promising initiatives, companies lack access to clear, practice-based transition pathways. "There are examples, but they are mostly product-related and quite focused," A1 shared. More comprehensive examples involving supply chain coordination and digital platforms for part reuse would be highly valuable. These don't require disclosure of sensitive process details but should include "high-level definitions of practices and example business models."

Organizational and technological reconfiguration

Transitioning to twin goals often means operating dual business models. "You have to manage it in parallel," A1 explained, noting that new processes like reverse logistics or servitization must run alongside existing, legacy operations. This parallelism creates internal strain and requires "specific governance structures" to coordinate the sustainability and digital sides of the transition. IT departments must evolve to handle expanded data-sharing needs and more intensive supply chain integration.

Overlooking the environmental impact of digital technologies

Interestingly, A1 observed that most companies are not yet considering the negative environmental impact of digital tools, perhaps because "enterprise systems have become commodity-like" and are seen as "non-resource-intensive" according to A1. However, A1 acknowledged that this might change with the adoption of more resource-intensive systems like generative AI.

Quick technological and regulatory shifts add to uncertainty

The fast-paced evolution of both technology and regulation complicates long-term planning. Companies are bombarded with new concepts like "digital product passports" and "sustainability control towers." As A1 put it: "Everything is just... so many concepts and technologies coming on top of each other." This, combined with uncertainty around international trade regulations and reporting standards, makes it hard for firms to know what to prioritize.

Summary interviewee A2**Digitalization status**

Despite recent progress, the integration of digital innovations into day-to-day operations still faces barriers. A2 highlights a case study from a public transport company where an AI solution was developed to detect the invasive Japanese knotweed near tracks, a costly problem. While the technical solution worked perfectly, it was not embedded into the standard asset management process. “There was no integration with the responsible business units,” which undermined the potential of the innovation. This, A2 emphasizes, is a clear example of the broader organizational fragmentation: digitalization efforts often operate in silos, separate from strategic or operational structures.

Sustainability status

In contrast to digitalization, sustainability is less developed and primarily driven by compliance. A2 observes, “The manufacturing sector is ahead of sectors like finance or retail, but mainly because of regulatory pressure, not intrinsic motivation.” European regulations, especially the Corporate Sustainability Reporting Directive (CSRD), are the key drivers. However, recent regulatory changes, such as the weakening and postponement of CSRD and CS3D requirements, have led many companies to delay sustainability efforts.

“There’s a sense of relief,” A2 notes, “and the response is: ‘good, now we don’t have to do more than what’s strictly necessary.’” This delay culture is concerning to A2, who sees it as a weakening of the twin transition vision overall.

Lack of integration

While the EU promoted the Twin Transition concept in 2020, A2 stresses that most companies still treat digitalization and sustainability as distinct tracks. “I’d say 90% see these as two separate domains. The definitions aren’t aligned, the scope is unclear, and each company creates its own interpretation.” As a result, there is limited motivation to integrate them, and even less clarity on how to do so.

This lack of shared understanding results in vague and often disconnected initiatives. The challenge lies not only in defining the twin transition but also in communicating a coherent narrative that resonates throughout the organization, especially one that translates into a compelling business case.

Economic return as the deciding factor

A2 points out that the economic argument is central: “If digitalization contributes to sustainability goals and leads to economic gain, such as cost reduction or operational efficiency, then it stays on the agenda. Otherwise, it disappears.” Especially in large manufacturing firms, investments are expected to deliver a return within 3–6 months, a short horizon that leaves little room for long-term sustainability investments without clear financial outcomes.

A2 refers to their own shift in mindset: once optimistic about achieving a “win-win” for people, planet, and profit, they now believe that unless economic returns are demonstrable, sustainability risks losing momentum. This is not only due to internal priorities but also shareholder expectations: “If there’s too much uncertainty, the board will say: don’t do it.”

Structural and cultural challenges

Organizational structures built around siloed departments make transformation especially difficult. Digitalization and sustainability are cross-cutting themes, but most companies are still structured around vertical ownership and accountability. “The moment a topic spans multiple departments, you have a problem,” says A2.

In the public transport company case, the disconnect between the innovation team and the core operations department illustrates this perfectly. According to A2, implementing the Twin Transition often requires process redesign, stakeholder coordination, and a broader cultural shift. But such change is time-consuming and perceived as risky, particularly by upper management.

There’s a notable contrast in how different organizational layers perceive transformation. A2 sees a willingness among technical teams to engage, but strategic leadership is often focused on risks, timelines, and capacity. If a transformation is not seen as a “must-have” or urgent it’s usually postponed or dismissed.

Ecosystem thinking

According to A2, in many cases, sustainability gains depend on collaboration across supply chains. An example is given of a project involving an insurance company and a car repair chain aiming to reuse components like bumpers from scrapped vehicles instead of ordering new ones. Such initiatives require data-sharing, logistics coordination, and cultural alignment.

Yet, confidentiality and competitive concerns, especially in the high-tech sector, hinder data sharing. However, A2 notes that technological solutions exist, including secure data exchange protocols and Digital Product Passports, which allow the sharing of essential product information without compromising IP or sensitive data. "Everyone's first reaction is privacy, security, but the enabling tools are there."

Need for proof of concept and shared roadmaps

One of the key barriers is the absence of proven strategies or best practices. According to A2, companies still operate in an exploratory phase. Even promising cases, such as the development of a sustainability reporting module by a Switzerland-based major tech platform, run into practical challenges. In that case, gathering emissions data for leased cars became contentious due to privacy concerns from users and a lack of obligations for suppliers to deliver detailed data. As a result, much reporting became fragmented and ad hoc.

Despite a desire for guidance, A2 warns that standardised roadmaps may not suit all companies, given the variety of contexts and challenges. The field still lacks empirical research into transformation strategies, whether to lead with digital, sustainability, or integrate both. "There's one conceptual paper proposing three development paths, but no one knows what actually works yet."

Cultural attitudes and resistance

Interestingly, A2 finds that digitalization now triggers less resistance than sustainability. "We've learned that not everyone loses their job when technology is introduced," and past fears (e.g., with RPA or AI) have given way to more realistic adoption strategies. Sustainability, however, remains more abstract and harder to operationalize, particularly the social and governance aspects of ESG.

Operational employees often don't relate to issues like boardroom diversity or executive bonuses, while CO₂ emissions are more tangible. Still, A2 believes the vagueness of sustainability creates discomfort and inaction. Meanwhile, without a clear economic incentive, the topic struggles to compete with more pressing business concerns.

Continuous evolvement

The twin transition remains a largely experimental domain. According to A2, most companies are still in the phase of discovering what it means, whether it's worth pursuing, and how it could benefit them. "There's a need for more storytelling, for pilot projects that demonstrate real value." Without a burning platform or visible benefits, companies (especially large, risk-averse ones) are unlikely to act decisively. The term itself, twin transition versus twin transformation, is also under debate. Some see it as a manageable roadmap, others as a complex and ongoing journey. In either case, the challenge is not only technological or regulatory, but deeply organizational, strategic, and cultural.

Summary interviewee P1

Status of the Twin Transition

Dutch high-tech manufacturing companies, particularly in the semiconductor sector, are actively engaged in both the digital and sustainability transitions, but the maturity levels vary significantly. According to P1, "The clients are fully engaged. It's high on the agenda for all of them." However, the extent and nature of involvement differ. Some companies are still focused on foundational efforts like removing legacy systems and establishing uniform platforms, while others are already exploring AI and GenAI to boost productivity and competitiveness.

Initially, sustainability efforts were product-focused, e.g., the carbon footprint of an iPhone, but companies are now also examining non-product domains like travel, energy usage, and internal operations. Circular initiatives, such as refurbishment and remanufacturing, are on the rise and are seen as long-term trends.

When it comes to strategy, P1 sees value in both generic and tailored approaches. While companies face shared regulatory demands that could be addressed via common roadmaps, their unique posi-

tions in the value chain, and their specific dependencies, require custom strategies.

Drivers for the Twin Transition

The competitive landscape plays a critical role in shaping digital strategies. Companies in more competitive segments tend to be more aggressive and innovative. “You’re more paranoid, so to speak. You focus more on differentiation.”

For the sustainability transition, regulation is the primary driver. P1 highlights the importance of upcoming regulations like CSRD, which have created a clear trajectory up to 2026–2027. “There is definitely a recognizable pattern, but it is mainly driven by regulation.” Beyond compliance, customer expectations are becoming increasingly influential. Many clients are demanding transparency and sustainability from their suppliers, especially concerning product-related emissions, which has a ripple effect through the value chain.

Implementation challenges

One significant challenge lies in the cost structure of digital initiatives. Both the high upfront implementation costs and the often-underestimated ongoing operational expenses are major concerns. “Sometimes the run costs end up being higher than the implementation costs,” especially in technologies like cloud or AI. This creates a constant balancing act: “You can only spend your money once.”

Another nuanced issue is the limited understanding of the environmental impact of digital technologies. While AI and IoT can enhance efficiency and reduce emissions, they also come with a heavy carbon footprint, particularly AI datacenters. “There is little transparency in the chain,” P1 notes, making it hard for companies to assess or take full responsibility for digital sustainability impacts.

A major obstacle across both transitions is talent. There is a twofold challenge: older systems require legacy skills that are becoming rare, while emerging technologies demand new capabilities that are in short supply and expensive. “It’s incredibly difficult,” P1 says. “The new generation isn’t interested in outdated technologies.” While reskilling is a hot topic, it’s not easy, due to both financial and motivational barriers.

Organizational changes

Furthermore, the organizational model itself is under pressure to change. With automation and AI reducing the need for human input in some processes, companies are rethinking structures, consolidating roles, and reconfiguring governance models. Traditional silos between business and IT are breaking down, and cross-functional collaboration is becoming the norm.

Culture and leadership heavily influence the pace and success of transition. Companies that support a learning culture, support experimentation, and invest in their people are more likely to succeed. “Ultimately, talent is the biggest driver for the transitions,” P1 emphasizes, noting that fear-based cultures or poor diversity and inclusion can hold back progress.

Summary interviewee P2

Progress and maturity in digitalization

According to P2, significant progress has been made in digitalization over the past five to ten years, especially in the semiconductor sector. Concepts like Digital Twins, once costly and immature, have become more feasible due to improved tools, increased interoperability (especially thanks to cloud adoption), and integration between PLM and enterprise systems. Despite this progress, companies are “not there yet.” Data quality remains a major challenge, and the human factor, conservatism and resistance to change, still plays a significant role. As P2 notes, “We are perhaps still a bit constrained by the past,” referring to the hype cycle that needs to be endured before full adoption.

Sustainability: on the agenda, but not always a priority

Sustainability is recognized, but often not prioritized due to the volatile nature of the industry. In semiconductors, trade-offs are frequently made between ESG goals and core business goals like increasing production or yield. As P2 puts it, “That R&D euro can only be spent once,” highlighting the difficulty in justifying ESG-related R&D over product development. There is visible effort, such as shifting machine transport from air to sea to reduce CO₂, improving energy efficiency per wafer, and increasing transparency in supply chains. However currently, “It might be 30% of the annual report, but not 30% of the

actual work.”

Cost and uncertainty in value

High implementation costs are a barrier, but so is the uncertainty around the return on investment, especially for ESG initiatives. Costs are not just technical but heavily organizational. “Technology and data may cost a lot, but the organizational implementation costs are maybe three to four times higher.” Challenges arise in rethinking decision-making processes and design choices, especially when existing methods have been in place for decades.

Interplay between digitalization and sustainability

Digital solutions like AI and cloud can have a sustainability footprint themselves. However, the ESG impact of digital technologies is not yet systematically integrated into decision-making. For example, “Python is not the most energy-efficient programming language, but everyone uses it.” P2 highlights the opportunity in making the energy and ESG impact of digital tools more transparent so designers can make informed trade-offs.

Need for roadmaps with flexibility

P2 sees value in both example roadmaps and tailored approaches. He argues that many companies may not be as unique as they think and would benefit from example transition paths, with enough flexibility to account for different starting points. “Everyone is on the same road from Rotterdam to Paris, but some are still in Rotterdam, others near the French border.”

Supply chain complexity

One of the most complex aspects is the integration across supply chains. While ESG goals increasingly influence supplier evaluation, many supplier relationships are still governed by technical specifications without sustainability considerations. Manufacturers that assemble products, due to their dominant position in the supply chain, have more leverage to drive sustainability throughout its supply chain, but even then, “There needs to be a balance between ESG goals and continuity.”

Quantification and KPIs

Environmental impacts like energy use and CO₂ are more easily quantified than social or governance aspects. Social sustainability, such as safe working environments or fair labor, is much harder to quantify and integrate into business cases. P2 points out the challenge: “Not everything that is measurable is comparable.”

Organizational and cultural change

The transitions require not just new skills but a new mindset. Integration between departments like R&D and manufacturing must improve, particularly around circularity and reuse. Yet, resistance remains: “People are by definition conservative.” While strategic layers often understand the importance of sustainability, the challenge lies in operational implementation, where real behavioral change is needed.

Summary interviewee P3

Sustainability in the high-tech sector is still developing

P3 observes that while high-tech companies, especially in the semiconductor industry, are becoming more engaged with sustainability, their focus is primarily on energy use and emissions during chip production. Issues like carbon reduction, energy efficiency, and emissions have surfaced multiple times in discussions with clients. However, sustainability often enters the picture from a compliance perspective rather than being fully integrated into business strategy. As P3 notes, “Many companies want to do something with sustainability, but often it’s compliance driven. When you double-click, not all of them have a clear value proposition connected to business value.”

Complex supply chains and risk management

A key challenge lies in managing complex, global supply chains. Companies face difficulties in collecting data from suppliers and assessing risks within their supply chains, such as exposure to critical or conflict minerals. These challenges are amplified by geopolitical tensions (e.g., the war in Ukraine),

which have made access to energy and raw materials more uncertain. As P3 explains, "A lot of emissions or risks companies have sat inherently in the raw materials and components they source, this is crucial."

Regulatory uncertainty and compliance burden

Legislation, especially from the EU (like CSRD), is both a driver and a source of concern. Although it aims to accelerate sustainability, companies struggle with its complexity and evolving nature. This creates uncertainty, which hinders strategic planning. "When legislation changes, unrest emerges. Companies wonder: what do I really have to do? Do I do this for compliance, or because I see value for my organization?" P3 highlights how recent regulatory shifts (e.g., the Omnibus amendment) gave companies more time but also reflected how unsettled the regulatory environment still is.

Defining a clear business case remains difficult

One of the most pressing challenges is the lack of clear business cases for sustainability and circularity, especially in the high-tech sector, where products rely on small but critical materials. Recycling complex chip components is technically challenging and often not economically viable yet. P3 notes that while companies in other sectors (e.g., consumer goods) can link sustainability to premium offerings, such models are less obvious in high-tech. "For small critical minerals, recycling is still complex. The business case is often not there yet."

Scope of responsibility: from factory to entire value chain

P3 emphasizes that companies must think beyond their own operations. Effective sustainability efforts require action across three pillars: internal operations (e.g., energy usage), product use phase (e.g., efficiency of chips), and supply chain impacts (e.g., sourcing of materials). "You can do a lot in your own operations, but a large part of the footprint lies in the supply chain, especially for chipmakers."

The digitalization-sustainability connection

While digitalization has the potential to enable sustainability (for example, through real-time energy management or better supply chain insights) quantifying these benefits remains a challenge. P3 observes that many organizations still struggle with basic data quality, making it hard to progress beyond first steps. "Use cases sound promising in theory, but quantifying exact savings or efficiency gains remains difficult."

Efficiency as a common denominator

According to P3, energy and material efficiency are the most widely embraced paths toward sustainability, partly because they align closely with business performance. Yet, P3 also warns against reducing sustainability to mere efficiency, reminding that broader responsibilities exist, including reducing pollution and ensuring responsible practices in communities and supply chains. "There is a strong overlap between common business sense and sustainability, but sustainability is more than that."

Social sustainability still underdeveloped

Finally, social sustainability is gaining attention but remains loosely defined. Whether it's about inclusive teams, fair working conditions in the supply chain, or minimizing environmental harm to communities, companies still need to clarify their approach. "You can't leave social sustainability undefined. It's about the right way of working in all its dimensions."

Summary interviewee M1**Lagging digital maturity across the sector**

Despite the hype around Artificial Intelligence and Industry 4.0, most companies remain at a much earlier stage of digital maturity. Using a six-level maturity level, M1 explains that most companies operate at level 2 or 3. They are still focused on conventional automation (Industry 3.0), not yet at levels where AI or data valorisation are feasible. "Even large semiconductor companies are stuck at level 3, with no interoperable data systems. They're not yet extracting maximum value from their data."

For smaller players, particularly Tier 2 and 3 suppliers, the situation is even more basic. Many still work with paper-based instructions, isolated systems, and no integration between ERP, PLM, and MES

systems, making any form of advanced digitalization nearly impossible.

Economic viability trumps ambition

High implementation costs aren't necessarily the main barrier, but rather, the uncertainty around economic returns is what holds companies back. The mindset is business-case-driven: investments must typically pay off within two to four years. "Nobody wants to build the most digital or sustainable factory in the world, they want something that gets them from A to B efficiently."

M1 gives the example of Neways, a supplier for ASML, which reuses parts from €300,000 cabinets. The value justifies the investment in refurbishment. By contrast, redesigning a €30 electric toothbrush for circularity simply doesn't pay off, consumers replace it rather than repair it.

Companies are hesitant because returns are uncertain, and digitalization projects have a reputation for risk. A1 cites examples of ERP or robotics projects costing over €1 million that fail to deliver ROI, creating a climate of distrust. "If even we at [the research institute] don't know what a digital product passport costs or delivers, companies certainly won't invest in it."

Fragmented and manual approaches to circularity

While sustainability is on the agenda, practical implementation, especially in circular economy strategies, is still in its infancy. Tracking product-level CO₂ data or component-level information is often done manually, requiring intensive labour.

"Many companies manage circularity with Excel sheets. With upcoming regulations, they'll need just as many people to manage return flows as to assemble the products."

High-complexity products, like ASML machines, present a logistical nightmare in circular terms. With components from over 50 suppliers, disassembly, identification, and qualification for reuse requires an automated, centralized approach, one that currently doesn't exist.

Unclear regulation and strategic trade-offs

Regulations around sustainability are often seen as burdensome, offering no direct business value. There's frustration about unclear or shifting regulatory landscapes, especially at the European level, and the lack of alignment between regulation and market incentives. "Being more sustainable doesn't necessarily make you more competitive. What is that unique selling point then really worth to the customer?"

Examples like Fairphone show that even when a product is ethically and sustainably made, consumers often still choose newer, shinier models after 2–3 years. In semicon, PFAS restrictions force redesigns that cost millions and take years, without improving machine functionality. Some companies face the dilemma: comply and lose market position, or maintain control points at the risk of non-compliance.

M1 points out how legal uncertainty delayed or even killed startups in plastics recycling, because regulations on recycled content were lacking or poorly enforced.

Supply chain power imbalance

Manufacturers that are assemblers or integrators hold significant power in supply chains and often do not incentivize their suppliers to innovate for sustainability. Suppliers operate on very small margins and won't adopt sustainable practices unless the assemblers are willing to pay for them. Even when suppliers manage to reduce material use or cost, assemblers may demand these savings be passed on, discouraging further innovation.

Technological changes vs long-term investments

The high pace of technological change contrasts sharply with the long investment cycles typical in manufacturing. Companies may be locked into outdated technologies because of previous capital investments. "You're still producing on existing machines until they die or the advantage of new tech becomes overwhelming."

M1 notes that although more sustainable technologies exist, adoption is slow because companies already invested in traditional production equipment.

Data, best practices, and shared learning are lacking

According to M1, many companies make decisions based on intuition rather than data due to lack of benchmarking or accessible best practices. Even within large companies, different departments don't

share knowledge. This hinders smarter decision-making and slows down the Twin Transition. M1 gives the example of how in one company, the Dutch site insisted on repurchasing a 30-year-old pump-model, while their French site had already been working with a newer version for five years with full satisfaction.

There's a need for ecosystems that support data sharing and shared innovation. M1 stresses that companies often see each other as competitors, even when they face the same challenges. In semi-con, for example, all firms need torque-controlled screw-fastening automation, but each tries to solve it alone. "We shouldn't think in terms of competing companies but competing global supply chains."

Human-centric change and workforce readiness

Technology shouldn't be seen as a 'technology push', it must be human-centric. Social sustainability matters, especially in terms of reskilling and job satisfaction. Automation can increase job quality if implemented properly. "A robot that takes over boring tasks can make room for more meaningful, innovative work."

Companies need to involve workers in transitions and train them. Otherwise, the risk is disengagement, or worse, resistance.

Strategic advice: start small, keep it simple M1 closes with pragmatic advice: start with small, visible successes. Don't try to revamp your entire sustainability or digital strategy overnight. "Go for the quick wins. Build experience. That creates momentum and motivation to keep evolving."

Summary interviewee M2

Digitalization: a broad disparity in maturity

Digitalization within the Dutch high-tech manufacturing sector is highly uneven. M2 describes a landscape marked by extremes: a handful of frontrunners, often larger companies or startups, and a vast majority of businesses that lag significantly behind. "It's very widespread. Some companies are very advanced, but the majority is still in the basics (in line with Rogers' innovation adoption curve), still using paper-based orders and drawings."

Larger companies tend to have more capacity to invest in innovation, staff training, and IT infrastructure. Startups often start digital-by-default, driven by new solutions tailored to specific industries. In contrast, many small and medium-sized enterprises (SMEs) lack the resources, people, or knowledge to get started. "There's a very large group that should be doing something but haven't even started."

Sustainability: parallel to digitalization, but often disconnected

The pattern around sustainability is similar: some companies take the lead, driven by anticipated regulation or internal motivation, while others wait passively. However, digitalization and sustainability are often approached in isolation. M2 observes that companies rarely connect the two transitions. M2 recalls a meeting with a company with a high digitization rate. But when confronted with upcoming regulations on circularity, the company had not considered the implications for the total value chain. "They realized circularity added a different dimension to the existing digitization in this chain."

Implementation costs and economic returns

The top two challenges companies face, high implementation costs and uncertain returns, are tightly interlinked. M2 describes them as part of a feedback loop: "It's a bit of a chicken-and-egg problem. If you can't demonstrate returns, you don't invest. But you need to invest to see any return."

M2 distinguishes between different "layers" of digitalization. The first involves basic systems like digital order handling. The next layer enables companies to certify and track the sustainability of their supply chains. Closing the loop by using 'remanufactured' components might be necessary for a circular economy, but this is a non-existing value chain (because buying new components in China is cheaper) according to M2.

This requires substantial investment, especially in sectors where suppliers are not yet aligned. Without clear market incentives or regulatory pressure, many companies hesitate to invest.

The role of regulation

According to M2, regulation can break the cycle of inaction, but only if it is clear, consistent, and enforced. "Somewhere, something has to break the cycle. And regulation is often the way to do that." Large companies like ASML, with significant influence over their supply chains, can use regulation to

their own advantage by driving change downstream.

However, M2 also points out that inconsistent implementation of regulations, particularly in the Netherlands, undermines confidence. “If you get the impression that the rules can change at the last minute, it’s hard to build on that.” M2 notes that Dutch policy often lags or wavers due to lobbying pressure, which makes it harder for companies to prepare or invest early.

European regulations are a more significant driver in many cases, especially for large, internationally active firms. Yet, M2 emphasizes that even then, the effects don’t always trickle down to SMEs, especially in fragmented sectors like maritime manufacturing. “In our region, the maritime sector for example is too fragmented to drive the transition collectively, there’s no ASML-like big player that can lead and enforce the way.”

Lack of transferable best practices and roadmaps

Despite the shared challenges, there is little standardization in how companies approach the Twin Transition. M2 sees a clear absence of sector-wide roadmaps or best practices. “Everyone is reinventing the wheel.”

This problem is amplified by the complexity of manufacturing chains. For example, changing the materials in a product for sustainability reasons often requires redesigning upstream processes and tools, which can only be done if data flows freely across the chain. In many cases, such data isn’t shared due to proprietary concerns or technical barriers. “You must look at the entire chain, from material design to product function. That’s not something one company can solve alone.”

Digitalization as a tool

A recurring theme in M2’s reflections is that digitalization should be understood as an enabler rather than a goal. It can support product and process innovation, traceability, and even new business models like product-as-a-service. But it must be implemented with a clear purpose in mind.

M2 shares a detailed example of a component designed with topology optimization and 3D printing to reduce material use, a clear sustainability gain. But getting such a component certified and integrated into existing production systems took a long time. “You can’t just say, ‘we’ll use a tool and we’re done.’ Every step in the chain needs to be adapted.”

Human capital

Digitalization also presents major human challenges. Many companies face a shortage of skilled personnel and rely on a few experienced workers whose practical knowledge is undocumented. “If someone has been assembling a product for 20 years and leaves, how do you transfer that knowledge?”

Digital tools could support knowledge retention and training, for instance, using augmented instructions or smart workstations, but these are rarely used due to high costs and limited awareness. “Companies are still too hesitant. But with a tight labor market, we’ll have to go there.”

Moreover, as business models change (e.g., towards maintenance and services), companies will need different types of employees. “You go from 20 people making things to 15 maintaining them, that’s a big internal shift.”

Summary interviewee M3

Uneven maturity

M3 sketches a “mixed picture” of digitalization in the Dutch high-tech sector. Larger companies were already building data science teams years ago and have made significant progress in adopting artificial intelligence. In contrast, smaller companies face more limitations: “They don’t have deep pockets,” making it difficult to build the required capabilities. For these firms, the core question is still: “What does AI actually mean for us, and what can we do with it?”

In many SMEs, there is a sense that something must be done, but they often lack understanding of what is needed and how to create value from digitalization. M3 states that the situation is similar when it comes to sustainability. The introduction of CSRD regulations has increased awareness, especially among large firms, but smaller firms struggle with the burden: “It creates a chicken-and-egg problem” because they aren’t yet required to report but lack the means to start building the systems for it according to M3.

Disconnect within the Twin Transition

In most companies, digitalization and sustainability are “still separate agendas.” M3 explains that while digital tools, like simulations and digital twins, can speed up R&D and reduce waste, their contribution to overall CO₂ reduction remains limited. “You might save some material by doing more in software, but it doesn’t make a big difference in your total carbon footprint.” In manufacturing-heavy environments, emissions are still largely driven by materials, transport, and fabrication.

Implementation costs and uncertain returns

The biggest barrier, according to M3, is the high short-term implementation cost. Hiring people for sustainability or expanding IT for digitalization can be a major hurdle, especially for mid-sized firms: “For a company with 200 employees, that’s a significant investment.” In contrast, expected economic returns, though important, play out more in the long term. Business cases are usually assessed over a 5–10 year horizon. As M3 puts it: “The first challenge is operational. The second is more about long-term accountability.” This timeline, combined with the lack of clear payback, causes hesitation.

Additionally, M3 expresses concern that stringent European sustainability regulations could put local companies at a disadvantage compared to competitors in regions like the U.S. “There, it’s more drill baby drill,” M3 notes, referencing a quote by Donald Trump. In the Netherlands, higher energy prices, partly due to decarbonization, have already created a competitive burden. This discrepancy undermines the “level playing field” and creates strategic dilemmas according to M3.

Skills gaps and uncertainty

Companies often don’t know what knowledge they need for the Twin Transition. Internally, there’s a lack of clarity on how to apply digital tools or what kind of staff to hire. “At [a midmarket semiconductor manufacturer], we had a ton of test data, but we didn’t know where to begin to use that data to improve development.” Similarly, on the sustainability side, companies struggle with collecting, validating, and interpreting non-financial data, especially across the supply chain. For example, verifying supplier data further down the chain is “incredibly complex.”

Moreover, there’s a lack of practical guidance or standard roadmaps. There are inspiring examples, but these are rarely applicable in high-tech manufacturing. “Chip products are so different that you cannot just copy-paste those examples.” Each company’s mix of hardware and software is so specific that “there are no ready-made solutions lying on the shelf.”

Organizational culture and resistance

Resistance within organizations differs across domains. In R&D, digitalization is generally seen as useful: “It’s a tool to learn faster and develop faster,” and once value becomes visible, resistance fades. However, sustainability is perceived more as a burden: “Even people who believed in the green agenda said: this is a lot of extra work.” Therefore, these efforts often need to be pushed top-down with strong executive sponsorship.

Successfully embedding digital roles requires structural support and a mandate. In the R&D context, this might involve creating new cross-functional teams focused on data use and development processes. In operations, digitalization is already progressing, e.g., through better tracking of test data by batch or product series, but both domains need to converge over time.

Despite broader societal concerns, M3 does not see job losses due to digitalization as a major issue in high-tech manufacturing. On the contrary, there’s a “screaming shortage” of qualified personnel. M3 believes AI will support, rather than replace, the creative and engineering work that defines this sector. “The human part of engineering will remain very important.”

Difficulty quantifying impact and building a business case

M3 highlights a key challenge: the difficulty of measuring what digitalization or sustainability efforts actually yield. “If we invest in AI, will we reduce product development from 14 to 8 months? Or just to 13?” These kinds of impacts are often intangible or delayed, creating uncertainty. As a result, companies hesitate to invest, thus failing to learn what the actual benefits could be. “It becomes a vicious circle,” M3 warns.

Furthermore, M3 warns about unrealistic expectations from AI and digital tools. “We’re in a bit of a digitalization hype,” M3 says, where companies feel they need to do something, without really knowing what or how. Tools like AI are often seen as “a holy grail,” but their usefulness depends entirely on the

quality of the company's data infrastructure, something many companies lack. "If your data is not good, the AI won't work," M3 explains. This basic insight is "not yet widely understood."

The quantification problem also applies to sustainability: firms struggle to balance what they should do for ethical reasons, what is required by regulation, and what has financial benefits. Without clear, quantifiable gains, companies often wait rather than act. Frequent changes in policy add to the complexity. If rules around sustainability shift or become less strict, such as the recent watering down of CSRD, companies may delay decisions. M3 explains that this uncertainty "creates delay, because companies don't know what to bet on."

Confidentiality and supply chain transparency

One powerful example of how supply chain expectations can drive sustainability action is provided by a Swedish high-tech company. As a major customer of [a midmarket semiconductor manufacturer], the Swedish high-tech company began requiring its suppliers to present substantiated sustainability plans in order to remain in their supply chain. "It came from a real conviction within [the Swedish high-tech company]," M3 recalls. This external pressure aligned with the midmarket semiconductor manufacturer's internal reporting efforts and created a mutually reinforcing effect. "That initiative strengthened the entire supply chain."

M3 believes that environmental data like energy or water use can usually be shared without giving away technical trade secrets. "You can separate the two," M3 argues. However, verifying data from suppliers and integrating it across long and specialized supply chains remains a huge challenge.

Differences across subsectors

Sustainability's strategic value varies across subsectors. In semiconductor manufacturing, performance and time-to-market dominate. "Sustainability is really a second or third factor," M3 notes. In medtech, broader societal benefits can be emphasized more, but those are often health-related rather than environmental. In aerospace, long product life cycles slow down innovation, even though sustainability is a major goal: "Planes last 30 to 50 years," so any transformation is necessarily slow.

B.2.4. Causal loop diagram

Identified relationships between the thirteen challenges of implementing the Twin Transition in the Dutch high-tech manufacturing sector, based on literature and on interviews.

Table B.5: Identified relationships between challenges based on the literature definitions and interview insights, including reasoning and categorization of link into positive or negative reinforcement. The direction of the causal links is from challenge A to challenge B.

Challenge A	Challenge B	Link reasoning	Link based on interviews	Positive or negative reinforcement
1. High implementation costs	2. Uncertainty in economic returns	High implementation costs make companies more concerned about ROI (Gulbrandsen-Dahl et al., 2024; Stucki et al., 2024; Kekkonen et al., 2023; Fouquet and Hippe, 2022; Elyasi et al., 2024)	High implementation costs increase ROI worries, visibility gaps add hesitance (A1)	Positive
1. High implementation costs	8. Skill training	High costs limit training investment (Gulbrandsen-Dahl et al., 2024; Breiter et al., 2024; Fouquet and Hippe, 2022; Ortega-Gras et al., 2021)	Hiring for sustainability or digital roles is costly (M3), skills development faces financial and motivation barriers (P1)	Positive
3. Lack of impacts understanding	7. Lack of quantification	Poor understanding of sustainability impact hinders quantification (Abilakimova et al., 2025; Spaltini et al., 2024a; Kürpick et al., 2023; Kren and Lawless, 2024; Kekkonen et al., 2023; Peças et al., 2023)	Digital sustainability impacts seen as minimal, metrics vague (P2, P3)	Positive
2. Uncertainty in economic returns	1. High implementation costs	Not confirmed nor contradicted	Lack of ROI clarity makes upfront costs feel riskier and heavier (M1)	Positive
4. Lack of example transition paths	5. Lack of tailored strategies	Not confirmed nor contradicted	No clear examples means no tailored strategies for context (A1, M2)	Positive
5. Lack of tailored strategies	4. Lack of example transition paths	Not confirmed nor contradicted	Custom strategies make standard pathways harder to generalize (A1, M2)	Positive
6. Evolving nature of Twin Transition	7. Lack of quantification	Changing tech & impacts make metrics unclear (Abilakimova et al., 2025; Spaltini et al., 2024a; Kürpick et al., 2024; Kren and Lawless, 2024; Kekkonen et al., 2023; Tabares et al., 2025; Findik et al., 2023)	Many concepts/tech confuse what to measure (A1)	Positive
6. Evolving nature of Twin Transition	12. Changing and double regulation	Rapid tech/regulation evolution keeps rules shifting (Kren and Lawless, 2024; Chatzistamoulou, 2023; Tabares et al., 2025)	Not confirmed nor contradicted	Positive
6. Evolving nature of Twin Transition	1. High implementation costs	Changing tech could lower costs over time (Sjödén et al., 2024; Chen et al., 2023; Kekkonen et al., 2023; Breiter et al., 2024; Benedetti et al., 2023)	Interviews show rising costs, not falling – so negative link not realistic	Not realized yet

Challenge A	Challenge B	Link reasoning	Link based on interviews	Positive or negative reinforcement
7. Lack of quantification	13. Compliance and competitiveness	No metrics makes balancing compliance/competitiveness harder (Abilakimova et al., 2025)	Firms delay compliance without metrics, slowing strategy (M3)	Positive
8. Skill training	9. Resistance against change	Skills gaps fuel employee resistance (Trevisan et al., 2024; Tabares et al., 2025)	Insecurity, undocumented legacy knowledge, change feels risky (M3)	Positive
10. Reorganisation structure	8. Skill training	New ways of collaborating require new skills (Sareen et al., 2023)	Cross-functional digital/sustainability work demands new capabilities (A2)	Positive
10. Reorganisation structure	9. Resistance against change	Org shifts meet pushback (Christmann et al., 2024)	Org change needs strong leadership or employees resist (M3)	Positive
11. Lack of social sustainability focus	9. Resistance against change	Poor social focus means employees feel neglected (Christmann et al., 2024; Sareen et al., 2023)	Not confirmed nor contradicted	Positive
12. Changing and double regulation	2. Uncertainty in economic returns	Stricter regulation may clarify ROI by driving market change (Spaltini et al., 2024a; Tabares et al., 2025)	Regulation can force action, break inaction cycles (M1, M2)	Negative
12. Changing and double regulation	13. Compliance and competitiveness	Shifting rules make balancing investment and competitiveness tricky (Spaltini et al., 2024b)	Firms unsure "what to bet on" with changing rules (M3)	Positive
13. Compliance and competitiveness	12. Changing and double regulation	Not confirmed nor contradicted	Firms delaying for competitiveness become unprepared for new rules (P3, A2)	Positive

B.3. Stacey Matrix application

Table B.6: Challenge categorization in the Stacey Matrix zones per interviewee following the zone definitions according to Stacey (2012).

Category	Requirements	Technology	Reasoning
Challenge 1			
Complex	Clear	Unknown	A1: costs affordable, but cost/return transparency for sustainability lacking.
Complex	Clear	Unknown	A2: investments need clear ROI, tools to show it missing.
Complicated	Clear	Unknown	P1: need is clear, tech known, but long-term costs unclear.
Complicated	Clear	Unknown	P2: ESG investment known, but high/uncertain costs.
Complicated	Clear	Known	P3: firms want sustainability, but defining business case is hard.
Complicated	Clear	Known	M1: need for business case clear, tech exists, returns must be fast.
Complicated	Clear	Known	M2: ROI uncertainty slows known tech adoption.
Complicated	Clear	Known	M3: high costs recognized, returns known to lag.
Challenge 2			
Complex	Clear	Unknown	A1: firms don't assess digital footprint.
Complex	Clear	Unknown	A2: sustainability vague, hard to operationalize.
Complicated	Clear	Known	P1: goal clear, tools to measure footprint missing.
Complex	Clear	Unknown	P2: ESG impacts not integrated systematically.
Complex	Clear	Unknown	P3: poor data, measurement lacking.
Complex	Clear	Unknown	M1: goals clear, but tools/data weak.

Category	Requirements	Technology	Reasoning
Complex	Clear	Unknown	M3: promising tools, but CO ₂ impact poorly understood.
Challenge 3			
Complex	Clear	Unknown	A1: tailored strategies lacking, few best practices.
Complex	Clear	Unknown	A2: no roadmap, firms self-navigate.
Complex	Unclear	Unknown	P1: goals/maturity vary, no single fit.
Complex	Clear	Unknown	P2: need for flexible yet standard roadmaps.
Complex	Unclear	Unknown	P3: no clear start point despite frameworks.
Complex	Clear	Unknown	M1: fragmented efforts, need for central solution.
Complex	Clear	Unknown	M2: no sector-wide roadmap, partial data sharing.
Complex	Clear	Unknown	M3: no clear roadmap; unique hardware/software mixes.
Challenge 4			
Chaotic	Unclear	Unknown	A1: flood of new concepts, unclear priorities.
Chaotic	Unclear	Unknown	A2: firms still defining TT meaning.
Complex	Unclear	Unknown	P1: shifting tech/rules; partial tools.
Complex	Unclear	Unknown	P2: evolving goals, immature tools.
Complex	Unclear	Unknown	M2: shifting rules, low trust in tools.
Challenge 5			
Complex	Clear	Unknown	A1: lack of quantification, poor KPIs.
Complicated	Clear	Unknown	P1: decisions hard to quantify, missing indicators.
Complex	Clear	Unknown	P2: social/governance impacts hard to measure.
Complex	Clear	Unknown	P3: energy/emissions ok, supply chain harder.
Complex	Clear	Unknown	M1: manual tracking, no scalable solution.
Complicated	Clear	Unknown	M3: impact benefits unclear despite KPIs.
Challenge 6			
Simple	Clear	Known	P1: skills/tech clear, but roll-out takes effort.
Complicated	Clear	Known	P2: reskill/mindset shift clear, tech known.
Complicated	Clear	Known	P3: integration needs clear, known tech.
Complicated	Clear	Known	M1: reskill/design known, but takes time.
Complicated	Clear	Known	M2: roles shift clear, tools known, adoption slow.
Complicated	Clear	Known	M3: upskilling clear, digital infra exists.
Challenge 7			
Complex	Unclear	Unknown	A2: sustainability vague, uncomfortable.
Simple	Clear	Known	P1: resistance linked to scale of change, manageable.
Simple	Clear	Known	P2: resistance expected, managing change is known.
Simple	Clear	Known	P3: human factor, culture/leadership solutions known.
Simple	Clear	Known	M1: disengagement risk, inclusion/reskill key.
Simple	Clear	Known	M3: digital easier once value shown, sustainability top-down push works.
Challenge 8			
Complicated	Clear	Known	A1: legacy/new models in parallel, governance challenge.
Complex	Clear	Unknown	A2: silos/cross-cuts need cultural change.
Complicated	Unclear	Known	P1: restructuring clear, targets vary.
Complicated	Unclear	Known	P2: integration needed, target models differ.
Complicated	Unclear	Known	P3: supply chain sustainability needs consistent action.
Complicated	Unclear	Known	M1: legacy lock-in slows restructuring.
Complicated	Unclear	Known	M2: digital tool roll-out slow, end model varies.
Challenge 9			
Complex	Unclear	Unknown	A2: social/governance least defined, hard to measure.
Complex	Unclear	Unknown	P1: no clear social sustainability methods.
Complex	Unclear	Unknown	P2: hard to compare/define, no integration method.
Chaotic	Unclear	Unknown	P3: social sustainability visible but vague.
Chaotic	Unclear	Unknown	M1: job satisfaction matters, but poorly defined.

Category	Requirements	Technology	Reasoning
Challenge 10			
Complicated	Clear	Known	A1: regulations clear but shifting.
Complex	Unclear	Unknown	A2: firms follow EU rules, frequent changes.
Complicated	Clear	Unknown	P1: compliance tools exist, align with competitiveness tricky.
Complicated	Clear	Unknown	P2: ESG vs business tension, tools exist but misaligned.
Complicated	Clear	Unknown	P3: EU laws evolving, compliance tools there but unclear.
Complicated	Unclear	Known	M1: costly regulation shifts, tools exist but alignment unclear.
Complicated	Unclear	Unknown	M3: EU rules may hurt competitiveness, strategy unclear.

Table B.7: Challenge categorization in Stacey Matrix zones with reasoning based on interview insights, alignment with literature findings and the zone definitions according to Stacey (2012). The literature insights are based on the literature descriptions of the challenges identified in Section 3.1.2.

Category	Requirements	Technology	Challenge	Reasoning	Alignment with literature
Complicated	Clear	Unknown	Challenge 1: High implementation costs and uncertain economic returns.	Requirements clear, tech known, but long-term costs/ROI uncertain (P1, M3, M2). Careful planning needed.	Medium; literature says objectives clear, but ROI models still evolving.
Complex	Clear	Unknown	Challenge 2: Sustainability impact of digital technologies poorly understood.	A1, P2, M3: lack of tools/data for ESG impact, so complex despite clear needs.	Yes; literature confirms no clear framework for digital sustainability trade-offs.
Complex	Clear	Unknown	Challenge 3: Absence of pathways and tailored strategies.	P3, M1, M2: unclear roadmaps, fragmented efforts, context varies.	Yes; literature shows tech known but missing best practices increase uncertainty.
Chaotic	Unclear	Unknown	Challenge 4: Evolving nature adds complexity.	A2, P2: unclear priorities, tech fit unclear — so chaotic.	Yes; literature confirms fast-changing requirements and tech create instability.
Complex	Clear	Unknown	Challenge 5: Lack of quantification complicates planning.	A1, M3, M1, P1: missing KPIs/tools, so tech alone is inadequate.	Yes; literature highlights lack of standardized metrics for progress.
Complicated	Clear	Known	Challenge 6: New skills needed.	P1–M3 agree reskilling is needed; mindset/integration make it complicated.	No; literature says it should be simple: skills are identified, training exists.
Simple	Clear	Known	Challenge 7: Employee resistance.	P1, P2, M1, M3, A2: resistance manageable, strategies known.	No; literature says it's complicated due to human behavior unpredictability.
Complicated	Unknown	Known	Challenge 8: Organizational restructuring.	Tech known, but varying end goals make requirements unclear (A1, P1, M2).	Yes; literature confirms restructuring is needed but requires expertise.
Chaotic	Unclear	Unknown	Challenge 9: Limited social sustainability attention.	P1, P2, M1: lack of definitions/clarity, so chaotic.	No; literature says it's complex, not chaotic: frameworks missing, integration unclear.

Category	Requirements	Technology	Challenge	Reasoning	Alignment with literature
Complicated	Unclear	Known	Challenge 10: Evolving regulation vs competitiveness.	A1, P1, M1, M3, P3: tech known, EU law evolving, partial clarity.	Yes; literature confirms regulatory uncertainty needs structured compliance.



Phase 2 materials

C.1. Literature review

C.1.1. Structured review: the PRISMA approach for identifying research articles

Identification

To ensure a comprehensive search, two major academic databases, Scopus and Web of Science, were selected. The rationale for selecting these databases is explained in Section 2.3.1. Search terms were developed to capture models supporting organizational transformation. Four categories of search terms were used. Term Type 1 indicates the presence of a model or tool, Term Type 2 specifies the model's purpose as decision-support, Term Type 3 focuses the scope on company-level applications (not inter-organizational or national-level), and Term Type 4 ensures the model addresses change or transformation, not just assessment. An overview of these four term types is provided in Table C.1.

Boolean operators were applied: OR was used within each term type (e.g., "Tool" OR "Model"), while AND was used between different term types (e.g., "Tool" AND "Decision Support") to refine the search.

As a result of the identification phase, 461 research articles were found through Scopus and 203 through Web of Science, based on keyword searches. The Scopus search was conducted between March 10 and 11, 2025, and the Web of Science search was completed on March 9, 2025. Additionally, two additional relevant papers were identified through snowballing.

Table C.1: Search terms used for the structured review to identify company-level decision-support transformation models.

Term Type 1	Term Type 2	Term Type 3	Term Type 4
Tool	Decision support	Organization	Change management
Model	Decision assistance	Corporate	Change strategy
Scheme	Decision making support	Enterprise	Change process
Framework	Decision aid	Firm-level	Transformation management
Roadmap	DSS	Company-level	Transformation strategy
Template	decision-support tool	Business level	Transformation process
Instrument	Choice support		Innovation implementation
	Choice assistance		Innovation integration
	Choice making support		Innovation adoption
	Choice aid		Technology adoption
			Process innovation

Screening

The screening phase aimed to refine the initial set of search results by applying predefined criteria to the titles, abstracts, and keywords of each article. These criteria helped ensure that only papers relevant to the research focus progressed to the next stage of the review process.

During this phase, three main conditions were used to filter the results. First, only articles that could be accessed in full text through university or Accenture resources were considered. Second, papers had to be written in English to be included. Third, bibliometric reviews were excluded from consideration. While these reviews offer insights into trends in academic attention over time, they do not support the development of decision-support tools and were therefore not suitable for this study.

As a result of applying these criteria, the number of research articles was reduced to 402. After removing duplicates, 364 relevant articles remained for further evaluation.

Eligibility

Following the screening phase, the eligibility assessment further narrowed down the selection of studies by applying more detailed, content-related criteria to the titles, abstracts, and keywords. This step focused on ensuring the papers were not only broadly relevant but also aligned with the specific goals and scope of the research.

The first set of considerations involved whether the paper proposed an organization-level transformation within a company. To meet this condition, the study needed to present a model or framework rather than merely offering a description. It also had to focus on the company level, excluding studies that addressed inter-organizational or highly aggregated levels, and it needed to address transformation rather than merely assessing the current state.

The second focus was on domain relevance. To be included, the model discussed in the paper had to be applicable to the manufacturing sector and be relevant to industrial production, rather than centered purely on social transformation.

The final criterion addressed the scientific domain of the article. Studies that were overly technical or focused solely on social aspects were excluded. Instead, eligible papers needed to take an interdisciplinary approach and align with the socio-technical scope of this research.

Applying these content-specific criteria reduced the number of relevant papers to 42. A second round of eligibility assessment was then carried out using the full text of the remaining papers, based on the same criteria. This final review further reduced the number of selected articles to 11.

Included

The final phase determined which papers would be included in the structured review. To incorporate practice-based organizational transformation models, two grey literature models were also included that adhere to the same criteria as the academic research articles. An overview of the authors, titles, and focus of both the academic and grey literature-identified articles can be found in Table C.2.

C.1.2. Structured review: identified academic literature

Table C.2: Overview of the selected papers with title and focus summary.

Author	Title	Focus
Academic literature		
Macedo et al. (2024)	Structuring and analyzing initiatives that facilitate organizational transformation processes: a socio-technical approach	Based on sociotechnical systems theory and design science research, the article developed a framework to structure and analyze organizational initiatives to improve information-intensive work in digital transformations. The framework is based on typical success factors of digital transformation across different company dimensions, which are then structured to fit the company's specific needs.
Huang et al. (2024)	Implementation of digital twins in the food supply chain: a review and conceptual framework	This study focuses on the potential of Digital Twins to address the main challenges of the food supply chain. It aims to establish a conceptual framework for its implementation based on innovation adoption theory and the TOE framework.
Utama et al. (2024)	A fuzzy multi-criteria approach for selecting open-source ERP systems in companies using fuzzy AHP and TOPSIS	The focus of the article is on selecting open-source ERP systems for companies. The article aims to provide a structured and reliable method for optimizing operations using open-source ERP systems.

Author	Title	Focus
Forcina et al. (2024)	Exploring Industry 4.0 technologies to improve manufacturing enterprise safety management: A TOPSIS-based decision support system and real case study	The research focuses on identifying the best Industry 4.0 technologies for safety management. It aims to identify and rank the most effective technologies.
Shukla and Adil (2021)	A four-stage maturity model of green manufacturing orientation with an illustrative case study	This paper focuses on developing a maturity model with initiative pathways that support companies in adopting green manufacturing practices.
Zhang and Gu (2021)	Towards micro-level green growth: a framework to recognize corporate growth status, path and adopt eco-innovations	This paper focuses on micro-level green growth at the corporate level by examining its meaning, growth stages, and pathways, and proposes a life cycle-based strategy to support the adoption of suitable eco-innovations.
Alshahrani (2020)	An intelligent and adaptive model for change management	This paper introduces an intelligent and adaptive model for change management that considers internal and external factors and uses a decision support system to provide feedback on management methods.
Xia et al. (2017)	Sustainable technology selection decision-making model for enterprise in supply chain: based on a modified strategic balanced scorecard	The paper focuses on sustainable technology selection using a modified strategic balanced scorecard that balances the sustainability dimensions well.
Hernández et al. (2016)	A DSS-Based Framework for Enhancing Collaborative Web-Based Operations Management in Manufacturing Supply Chains	This paper explores how a decision support system (DSS) can improve web-based collaboration and operations management in manufacturing supply chains.
Chinoda and Kruger (2012)	An analytical hierarchy process (AHP) approach to modeling corporate climate change response	A structured approach to support complex decision-making in response to the risks and opportunities posed by climate change.
Deif (2011)	A system model for green manufacturing	A structured system model for guiding manufacturing enterprises through the assessment, planning, implementation, and sustainment of green manufacturing practices.
Grey literature		
Accenture (2020)	Nordic Circular Economy Playbook	Guides manufacturing companies through a structured transformation toward circular economy practices.
Directorate-General for Internal Market, Industry, Entrepreneurship and SMEs (GROW.D.2) (2022)	Blueprint for the development of transition pathways	Supports industrial ecosystem stakeholders in developing transition pathways for the Twin Transition using a structured guide.

Table C.3: Comparison of frameworks/tools by function and structure.

Author	Function	Structural characteristics
Macedo et al. (2024)	Structure relevant transformation success elements	Map elements across three domains (work system, support process, contextual conditions) and identify links between the elements (direct, reverse, bidirectional relationship) and create a visual diagram of all the links.
Macedo et al. (2024)	Prioritization of actions based on multicriteria evaluation	Prioritization grid that allows companies to select the criteria relevant for them (relevance, feasibility, expected impact), to tailor the success factors to their own goals. However, this is flexible and the weighting of criteria is left up to the company.
Macedo et al. (2024)	The framework is adaptive to the specific company context	Inclusion of many elements that can be considered, so that the company can select the relevant ones for their situation.
Huang et al. (2024)	The framework is adaptive to transition scale	The combination of an initiation phase (setting goals) and a technology assessment phase (assessing resource gaps) allows for determining readiness for small-scale or large-scale transformation

Author	Function	Structural characteristics
Huang et al. (2024)	The framework supports identification of the right technologies to facilitate the goals	The framework contains a technology assessment stage: current technology assessment, identify technology gaps, conduct technology preparation
Utama et al. (2024)	The framework supports transforming uncertain and subjective criteria into clear requirements	The framework uses a fuzzy AHP (analytic hierarchy process): pairwise comparison to identify the relative importance and establish weighted criteria
Utama et al. (2024)	The framework supports quantitative decision-making based on an alternative solution ranking	The framework uses TOPSIS to rank alternatives from ideal to least preferred, based on the similarity to the ideal solution in a decision matrix
Forcina et al. (2024)	The framework supports a structured review of alternatives	The framework uses a flowchart to select technology alternatives based on yes/no decisions
Forcina et al. (2024)	The framework supports quantification of the impacts of the alternatives chosen through the flowchart	The framework uses TOPSIS to rank alternatives from ideal to least preferred, based on the similarity to the ideal solution by assigning scores from 1 to 5
Shukla and Adil (2021)	The framework distinguishes four levels of maturity in green manufacturing	The framework supports companies in assessing their current level of maturity and identifies pathways for companies to move with green initiatives from one maturity stage to the next by identifying management dimensions that support green manufacturing at different levels of maturity
Shukla and Adil (2021)	The framework supports different paces of increasing the green manufacturing maturity	The framework's maturity stages represent a gradual transformation path from basic compliance to green manufacturing leadership, and companies can progress at their own pace through the different stages.
Zhang and Gu (2021)	The framework supports selection of the right eco-innovations	The framework provides an overview of eco-innovations and maps their expected economic performance and expected environmental performance based on literature findings (performance is qualitative: direction, e.g. reduced, higher, etc.)
Zhang and Gu (2021)	The framework supports environmental performance assessment over the innovation lifecycle	The framework integrates LCA to quantitatively assess the full environmental impacts of an innovation
Zhang and Gu (2021)	The framework supports quantitative progress monitoring	The framework uses quantitative KPIs (net profit, environmental footprint, corporate eco-efficiency)
Zhang and Gu (2021)	The framework supports economic return forecasting	The framework uses cost-benefit analysis and life cycle costing of eco-innovations
Zhang and Gu (2021)	The framework supports choice of different growth paths	The framework proposes seven growth paths (e.g. genuine green growth path, acceptable green growth path, grey growth path, uncertain growth path) based on the gap between current indicator status and target goals
Alshahrani (2020)	The framework supports choice of a best alternative for a company's specific situation	The framework uses a formula to evaluate alternatives based on actual inputs on the company's situation for internal (human resources, products, budget) and external (competition, economic situation) factors
Xia et al. (2017)	The framework provides a method to evaluate technologies using multiple sustainability dimensions	The framework maps objectives for environmental, social and economic sustainability by integrating them with existing balanced scorecard dimensions (economic sustainability and financial, social sustainability and customer, environmental and learning & growth)
Xia et al. (2017)	The framework supports alternative comparison through aggregated, comparable scores	The framework uses AHP (analytical hierarchy process) to normalize scores for different metrics so alternatives can show their relative performance
Hernández et al. (2016)	The framework is adaptive to the specific company context	The framework uses ERP system data as inputs (materials, capacity, job costing, inventory and workforce)
Chinoda and Kruger (2012)	The framework is adaptive to the specific company context	The framework is structured around four maturity stages, allowing companies to rank sub-goals within each maturity cluster based on their specifics
Chinoda and Kruger (2012)	The framework supports choice of different growth paths	The framework uses AHP to rank sub-goals within a certain climate change response cluster

Author	Function	Structural characteristics
Chinoda and Kruger (2012)	The framework provides a step-by-step structured progress approach	The Climate Change Response ladder structures the progress in four distinct clusters with sub-goals that follow each other
Deif (2011)	The framework is adaptive to the specific company context	The framework contains an assessment layer where the company can assess if they are black, brown or grey (sustainability maturity), which tailors the resulting 'paint it green' actions to the sustainability maturity level
Deif (2011)	The framework contains a preparation phase that assesses the available resources	The framework contains a preparation phase that assesses available resources
Deif (2011)	The framework supports quantification of the sustainability impacts	The framework uses a Green Manufacturing Metric that aggregates multiple green manufacturing metrics into a single value (e.g., waste, energy use)
Accenture (2020)	The tool supports companies in structuring the business case for circular initiatives	The value case tool calculates high-level business cases for implementing different circular practices at various levels, using company-specific input
Accenture (2020)	The tool supports creating a step-by-step roadmap	The roadmap development tool contains a template with standard steps that companies can adapt based on their ambitions and available resources
Accenture (2020)	The tool is adaptive to the specific context of a company (size, maturity, pathway, etc.)	Each support tool provides guidance on key considerations and uses the company's own input to create concrete actions and insights
Accenture (2020)	The tool supports different starting points for companies	The tool has three integrated assessment tools to analyze the gap between the current and desired situation: capability, technology, and culture maturity assessments
Directorate-General for Internal Market, Industry, Entrepreneurship and SMEs (GROW.D.2) (2022)	The framework guides companies in a stepwise manner through developing a Twin Transition roadmap	The framework includes questions that a company must answer to progress through the Twin Transition in sequential order (each question builds on the previous one)
Directorate-General for Internal Market, Industry, Entrepreneurship and SMEs (GROW.D.2) (2022)	The framework supports progression through multiple dimensions of the Twin Transition	The framework integrates seven dimensions relevant to the Twin Transition (sustainable competitiveness, regulation, social dimension, infrastructure, skills, etc.), each with maturity stages relevant to the Twin Transition

Table C.4: Overview of reference models and their adaptation to the decision-support tool requirements.

Reference	Function literature model	Structural characteristics literature model	Functional requirement decision-support tool	Adapted structural characteristics to decision-support tool
Macedo et al. (2024)	Structure relevant transformation success elements	Maps elements across three domains (work system, support process, contextual conditions), identifies their relationships (direct, reverse, bidirectional), and visualizes them in a diagram.	The tool enables assessment for various sustainability dimensions for digital technologies used in high-tech manufacturing.	The tool maps impacts across multiple sustainability dimensions and also identifies links between the different dimension-impacts, all in a visual map
Macedo et al. (2024)	Prioritization of actions based on multicriteria evaluation	Prioritization grid that allows companies to select the criteria relevant for them (relevance, feasibility, expected impact), to tailor success factors to company-specific goals. However, this is flexible and the weighting of criteria is determined by the company.	The tool allows companies to compare alternative investment paths based on sustainability and cost-effectiveness.	The tool has a prioritization grid that uses a multi-criterion weighting (weighting decided by the company) to make alternative investment paths clear

Reference	Function literature model	Structural characteristics literature model	Functional requirement decision-support tool	Adapted structural characteristics to decision-support tool
Macedo et al. (2024)	The framework is adaptive to the specific company context	Inclusion of many elements that can be considered, so that the company can select the relevant ones for their situation.	The tool is adaptive to the specific context of a specific Dutch high-tech manufacturing company.	The tool includes a large set of different digital transformation technologies at different levels of advancement, making it adaptable to varying levels of maturity and manufacturing processes
Huang et al. (2024)	The framework is adaptive to transition scale: it can be used for small-scale pilot projects and it can be used for a broader transformation, depending on readiness and strategy	The combination of an initiation phase (setting goals) and a technology assessment phase (assessing resource gaps) allows for determining readiness for small-scale or large-scale transformation	The tool allows for different paces of transformation, ranging from incremental to radical.	Based on the digital maturity of a company, the sustainability maturity step can be small or large
Huang et al. (2024)	The framework supports identification of the right technologies to facilitate the goals	The framework contains a technology assessment stage: current technology assessment, identify technology gaps, conduct technology preparation	The tool identifies the resources needed for different implementation dimensions	The tool includes a current situation assessment, assesses which resources are needed for the goal and identifies the gap between the current and desired situation in terms of resources
Utama et al. (2024)	The framework supports transforming uncertain and subjective criteria into clear requirements	The framework uses a fuzzy AHP (analytic hierarchy process): pairwise comparison to identify the relative importance and establish weighted criteria	The tool enables assessment for various sustainability dimensions for digital technologies used in high-tech manufacturing.	The tool can use fuzzy AHP to quantify the social sustainability dimension
Utama et al. (2024)	The framework supports quantitative decision-making based on an alternative solution ranking	The framework uses TOPSIS to rank alternatives from ideal to least preferred, based on similarity to the ideal solution in a decision matrix	The tool allows companies to compare alternative investment paths based on sustainability and cost-effectiveness.	The tool uses TOPSIS closeness coefficients to show side-by-side comparisons of alternatives
Forcina et al. (2024)	The framework supports a structured review of alternatives	The framework uses a flowchart to select technology alternatives based on yes/no decisions	The tool allows companies to compare alternative investment paths based on sustainability and cost-effectiveness.	The tool uses a flowchart to identify suitable digitalization steps based on the company's digital maturity and sustainability goals
Forcina et al. (2024)	The framework supports quantification of the impacts of the alternatives chosen through the flowchart	The framework uses TOPSIS to rank alternatives from ideal to least preferred, by assigning scores from 1 to 5 based on similarity to the ideal solution	The tool allows companies to compare alternative investment paths based on sustainability and cost-effectiveness.	The tool uses TOPSIS to determine how close the solutions are to the ideal situation (e.g., maximum sustainability impact, maximum cost-effectiveness)

Reference	Function literature model	Structural characteristics literature model	Functional requirement decision-support tool	Adapted structural characteristics to decision-support tool
Forcina et al. (2024)	The framework supports quantification of the impacts of the alternatives chosen through the flowchart	The framework uses TOPSIS to rank alternatives from ideal to least preferred, by assigning scores from 1 to 5 based on similarity to the ideal solution	The tool supports side-by-side comparisons of digitalization options based on sustainability trade-offs.	The tool uses TOPSIS closeness coefficients to show side-by-side comparisons of alternatives
Shukla and Adil (2021)	The framework distinguishes four levels of maturity in green manufacturing	The framework supports companies in assessing their current level of maturity and identifies pathways for companies to move with green initiatives from one maturity stage to the next by identifying management dimensions that support green manufacturing at different levels of maturity	The tool allows for different starting points in the Twin Transition pathway depending on the level of digital and the level of sustainability maturity	The tool has multiple standard transition pathways that companies can choose to follow depending on their context and ambitions that guide them through the digital and sustainability maturity stages
Shukla and Adil (2021)	The framework supports different paces of increasing the green manufacturing maturity	The framework's maturity stages represent a gradual transformation path from basic compliance to green manufacturing leadership, and companies can advance at their preferred pace through the stages.	The tool allows for different paces of transformation, ranging from incremental to radical.	The tool connects digital and sustainability maturity through incremental steps, which can be done quickly or slowly depending on the company's preferences.
Zhang and Gu (2021)	The framework supports selection of the right eco-innovations to support the companies green/economic goals	The framework provides an overview of eco-innovations and maps their expected economic performance and expected environmental performance based on literature findings (performance is qualitative: direction, e.g., reduced, higher, etc.)	The tool allows companies to compare alternative investment paths based on sustainability and cost-effectiveness.	The tool gives an overview of the potential economic and sustainability performance impacts (e.g., cost savings and recovery of waste)
Zhang and Gu (2021)	The framework supports environmental performance assessment over the innovation lifecycle	The framework integrates LCA to quantitatively assess the full environmental impacts of an innovation	The tool shows both the direct and indirect sustainability impacts of digital tools.	The tool uses LCA to assess the direct (during use) and indirect (procurement and disposal) environmental impacts
Zhang and Gu (2021)	The framework supports quantitative progress monitoring	The framework uses quantitative KPIs (net profit, environmental footprint, corporate eco-efficiency)	The tool provides quantitative KPIs for tracking sustainability progress linked to digital transformation.	The tool uses aggregated KPIs for each of the sustainability dimensions (economic, environmental, social)
Zhang and Gu (2021)	The framework supports economic return forecasting	The framework uses cost-benefit analysis and life cycle costing of eco-innovations	The tool includes projected implementation costs of digital technologies (e.g., AI, cloud) in a Twin Transition context.	The tool uses cost-benefit analysis to estimate the financial returns of digital technologies for sustainability

Reference	Function literature model	Structural characteristics literature model	Functional requirement decision-support tool	Adapted structural characteristics to decision-support tool
Zhang and Gu (2021)	The framework supports choice of different growth paths	The framework proposes seven growth paths (e.g., genuine green growth path, acceptable green growth path, grey growth path, uncertain growth path) based on the difference between the status of indicators and the goals for those indicators	The tool allows for different paces of transformation, ranging from incremental to radical.	The tool provides a step-by-step approach for incremental transformation, which may be completed in parallel or through step-skipping for accelerated transformation
Alshahrani (2020)	The framework supports choice of a best alternative for a company's specific situation	The framework uses a formula to evaluate alternatives based on actual company-specific inputs across internal (human resources, products, budget) and external (competition, economic situation) factors	The tool is adaptive to the specific context of a specific Dutch high-tech manufacturing company.	The tool uses company-specific inputs on digital maturity, sustainability maturity, size, supply chain position, and transformation preferences, and applies a weighted criteria model to recommend digital technologies for achieving sustainability goals
Xia et al. (2017)	The framework provides a method to evaluate technologies using multiple sustainability dimensions	The framework maps objectives for environmental, social and economic sustainability by integrating them with existing balance scorecard dimensions (economic sustainability and financial, social sustainability and customer, environmental and learning & growth)	The tool enables assessment for various sustainability dimensions for digital technologies used in high-tech manufacturing.	The tool integrates sustainability dimensions into an existing model in support of broader business objectives when evaluating digital technologies
Xia et al. (2017)	The framework supports alternative comparison through aggregated, comparable scores	The framework uses AHP (analytical hierarchy process) to normalize scores for different metrics so alternatives can show their relative performance	The tool supports side-by-side comparisons of digitalization options based on sustainability trade-offs.	The tool uses AHP to create composite scores for each sustainability dimension impact of a digital technology, integrating positive and negative impacts into a single score
Hernández et al. (2016)	The framework is adaptive to the specific company context	The framework uses ERP system data as inputs (materials, capacity, job costing, inventory and workforce)	The tool identifies the resources needed for different implementation dimensions	The tool uses real input data to assess resource demands for digital technologies
Chinoda and Kruger (2012)	The framework is adaptive to the specific company context	The framework has a 'Climate Change Response ladder' with climate change actions in four standard maturity stages, allowing companies to rank sub-goals within each maturity cluster based on their specifics	The tool is adaptive to the specific context of a specific Dutch high-tech manufacturing company.	The tool has standard sustainability and digital maturity phases for the Dutch high-tech manufacturing sector, with selectable progression options
Chinoda and Kruger (2012)	The framework supports choice of different growth paths	The framework uses AHP to rank sub-goals within a certain climate change response cluster	The tool supports side-by-side comparisons of digitalization options based on sustainability trade-offs.	The tool uses AHP to rank the best digital technologies to obtain the sustainability goals

Reference	Function literature model	Structural characteristics literature model	Functional requirement decision-support tool	Adapted structural characteristics to decision-support tool
Chinoda and Kruger (2012)	The framework supports choice of different growth paths	The framework uses AHP to rank sub-goals within a certain climate change response cluster	The tool enables assessment for various sustainability dimensions for digital technologies used in high-tech manufacturing.	The tool uses AHP to rank qualitative and quantitative sustainability impacts of digital technologies
Chinoda and Kruger (2012)	The framework provides a step-by-step structured progress approach	The Climate Change Response ladder structures the progress in four distinct clusters with sub-goals that follow each other	The tool links digitalization efforts to corresponding sustainability goals in a stepwise format.	The tool uses different sustainability and digital maturity phases for stepwise progression in sustainability parallel to digital progress
Deif (2011)	The framework is adaptive to the specific company context	The framework contains an assessment layer where the company can assess whether they are black, brown, or grey (sustainability maturity), which tailors the resulting "paint it green" actions to the sustainability maturity level	The tool is adaptive to the specific context of a specific Dutch high-tech manufacturing company.	The tool uses inputs on the company's digital and sustainability maturity to provide a digital technology recommendation to obtain the sustainability goals
Deif (2011)	The framework contains a preparation phase that assesses the available resources	The framework assesses the requirements and improvement for material, energy, process and technology	The tool identifies the resources needed for different implementation dimensions.	The tool determines the resource gap between the current status and the desired goal
Deif (2011)	The framework supports quantification of the sustainability impacts	The framework uses a Green Manufacturing Metric that aggregates multiple green manufacturing dimensions into a single metric (e.g., waste, energy use)	The tool provides quantitative KPIs for tracking sustainability progress linked to digital transformation.	The tool aggregates sustainability metrics into a few clear quantitative KPIs
Accenture (2020)	The tool supports companies in structuring the business case for circular initiatives	The value case tool calculates high-level business cases for implementing different circular practices at different levels, using company input	The tool includes projected costs of implementing digital technologies (e.g., AI, cloud) in a Twin Transition context.	The tool uses company input on expected gains and costs to create a structured dashboard. The tool emphasizes generating custom scenarios over providing fixed estimates. This allows for scenario testing by changing input assumptions.
Accenture (2020)	The tool supports companies in structuring the business case for circular initiatives	The value case tool calculates high-level business cases for implementing different circular practices at different levels, using company input	The tool allows companies to compare alternative investment paths based on sustainability and cost-effectiveness.	The tool uses company input on expected gains and costs to create a structured dashboard. The tool emphasizes generating custom scenarios over providing fixed estimates. This allows for scenario testing by changing input assumptions.

Reference	Function literature model	Structural characteristics literature model	Functional requirement decision-support tool	Adapted structural characteristics to decision-support tool
Accenture (2020)	The tool supports creating a step-by-step roadmap	The roadmap development tool contains a template that includes standard steps that companies can tailor based on their ambitions and available resources	The tool links digitalization efforts to corresponding sustainability goals in a stepwise format.	The tool has open areas that a company can fill in based on their own preferences and context
Accenture (2020)	The tool is adaptive to the specific context of a company (size, maturity, pathway, etc.)	Each support tool provides a structure outlining key considerations and uses the company's own input to create concrete actions and insights	The tool is adaptive to the specific context of a specific Dutch high-tech manufacturing company.	The tool has open areas that a company can fill in based on their own preferences and context
Accenture (2020)	The tool supports different starting points for companies	The tool has three assessment tools integrated to analyze the gap between the current and desired situation: capability, technology, and culture maturity assessments	The tool allows for different starting points in the Twin Transition pathway depending on the level of digital and the level of sustainability maturity.	The tool allows for different combinations of digital and sustainability maturity and defines pathways accordingly
Directorate-General for Internal Market, Industry, Entrepreneurship and SMEs (GROW.D.2) (2022)	The framework guides companies in a stepwise manner through developing a Twin Transition roadmap	The framework has questions that a company needs to answer to progress in the Twin Transition in sequential order (each question builds on the previous)	The tool links digitalization efforts to corresponding sustainability goals in a stepwise format.	The tool defines consecutive steps to guide the Dutch high-tech manufacturing sector through the Twin Transition
Directorate-General for Internal Market, Industry, Entrepreneurship and SMEs (GROW.D.2) (2022)	The framework supports progression through multiple dimensions of the Twin Transition	The framework integrates seven dimensions that are relevant to the Twin Transition (sustainable competitiveness, regulation, social dimension, infrastructure, skills, etc.), each with maturity stages for the Twin Transition	The tool enables assessment for various sustainability dimensions for digital technologies used in high-tech manufacturing.	The tool has an axis that distinguishes environmental, social, and economic sustainability stages

C.2. Interviews

C.2.1. Survey questions

This survey will serve as the basis for our interview conversation. It should take no more than ten minutes to complete. Your responses will help tailor the discussion to the most relevant topics.

Goal of this survey and the interview: to specify the literature findings on the key requirements for a decision-support tool that will help Dutch high-tech manufacturing companies in advancing in the Twin Transition.

Definition of the Twin Transition in this study: The Twin Transition refers to the simultaneous shift towards sustainability (environmental, social and economic) and digitalization.

Definition of the high-tech sector in this study: High-tech manufacturing is a subset of the manufacturing industry that focuses on producing advanced technological products using innovative techniques, processes, and materials. The high-tech sector comprises sub sectors such as semi-conductor, nanotechnology, advanced materials and medical devices production.

Scope of the study:

- Geographical: only high-tech manufacturing companies in the Netherlands are considered.
- Company size: LEs (non-SME, > 500 employees, >50 million turnover)
- Process boundaries: company-level, only the processes with the high-tech manufacturing site are considered (not inter-company, but only intra-company processes)

Please fill in your full name.

What is your current role/job title? Please fill in all relevant roles.

Based on the 10 challenges outlined below, a set of functional and structural requirements for the decision-support tool has been identified. During the interview, we'll focus on the key requirements that are most relevant based on your input and categorization of these requirements. For your reference, here are the 10 key challenges identified through literature review and interviews related to implementing the Twin Transition in the Dutch high-tech manufacturing sector:

1. **High implementation costs and uncertain economic returns** Dutch high-tech manufacturing companies hesitate to invest in the Twin Transition due to high implementation costs and uncertainty about economic returns. The risk of unclear payback often outweighs the potential benefits of digitalization and sustainability.
2. **High implementation costs and uncertain economic returns** Dutch high-tech manufacturing companies hesitate to invest in the Twin Transition due to high implementation costs and uncertainty about economic returns. The risk of unclear payback often outweighs the potential benefits of digitalization and sustainability.
3. **Lack of standard Twin Transition pathways and need for tailored approaches** Dutch high-tech manufacturers face a dual challenge: there are no clear, sector-specific transition pathways to follow, but at the same time, companies require flexible strategies that reflect their unique operational contexts and maturity levels.
4. **Constantly evolving nature of the Twin Transition** The Twin Transition is changing itself: new technologies and shifting sustainability expectations continuously emerge. For Dutch high-tech firms, this creates complexity, as they must adapt while still managing legacy systems.
5. **Unquantified decisions complicate long-term planning** In the Dutch high-tech sector, it remains difficult to measure and track sustainability benefits (especially social sustainability) or digital progress (lack of KPIs), making long-term planning and investment decisions highly uncertain.
6. **New skill demands for companies and employees** Successfully implementing the Twin Transition requires Dutch high-tech manufacturers to build new skills across digital, sustainability, and interdisciplinary areas. But limited internal expertise, legacy systems, and unclear needs for capabilities slow this development.
7. **Resistance from employees due to extensive change** In Dutch high-tech firms, employee resistance (especially around sustainability) can arise from uncertainty, fear of change, or a lack of perceived relevance.
8. **Need for organizational restructuring** The Twin Transition requires Dutch high-tech companies to break down internal silos and stimulate collaboration between business, IT, and sustainability teams.
9. **Insufficient focus on social sustainability** While environmental and economic sustainability are often emphasized, social sustainability receives far less attention in Dutch Twin Transition strategies. This is mainly because it's harder to define, measure, and connect to digitalization efforts.
10. **Navigating evolving regulation while preserving competitiveness** Dutch high-tech manufacturers face a balancing challenge: the most relevant regulation (CSRD, CS3D) is difficult to balance with remaining competitive on a global playing field. This is made even more challenging by changing regulation.

Please categorize these functional requirements (what should the tool do?)

	Must-have	Should-have	Could-have	Won't have
The tool provides insight into the financial risks and returns of Twin Transition investments				
The tool maps the positive and negative sustainability impacts of digital technologies used in the Dutch high-tech manufacturing sector				
The tool maps the next steps of the sustainability transition specific to the Dutch high-tech manufacturers				
The tool is adaptive to the specific context of a specific Dutch high-tech manufacturing company				
The tool enables quantification of Twin Transition-related decisions and their long-term effects				

Please categorize these structural requirements (what should the tool do?)

	Must-have	Should-have	Could-have	Won't have
The tool uses cost-benefit analysis				
The tool employs standardised KPIs to compare technologies' impact				
The tool employs LCA to assess the direct and indirect sustainability impacts				
The tool incorporates digital and sustainability maturity models				
The tool uses a weighting system to include their priorities				
The tool uses open areas that companies can fill in with their own input				

C.2.2. Interview protocol

Begin with an introduction of myself and the research. Explain that the goal is to identify requirements for the to-be designed decision-support tool for implementing the Twin Transition for Dutch high-tech manufacturing companies. Emphasize that the interviewee's experiences will be valuable. Ask if the interviewee has any questions about the consent form. Repeat the consent elements previously shown to the interviewee during the before provided and signed consent-form. Ask for a brief introduction of the interviewee. Verify the name and current role of the interviewee.

1. Starting questions

These initial questions aim to provide context and gather the interviewee's perspective:

1. *Can you briefly describe your role and experience in/with the Dutch high-tech manufacturing sector?*
2. *Can you please describe your current approach to developing digital and sustainability strategies for clients?*
 - *What kind of tools, frameworks or methodologies do you currently use?*
 - *Can you describe a recent project where you wished you had a decision-support tool?*

2. What are you looking for in a tool?

These questions are to understand what kind of tools or frameworks the interviewee usually employs, to figure out what kind of characteristics the to-be developed tool should have to fit in the working-style of the interviewees.

- *What is the main reason that you would like to use a decision-support tool?*

- It helps you think in a more structured way
- It helps you think about multiple dimensions at the same time
- Etc.
- At what moment would you use a tool?
 - In preparing for a client conversation
 - With a client as a ‘talking piece’
- How do these tools look like?
 - Excel
 - Flowchart
 - Assessment model
 - Etc.

3. Literature requirement questions

Functional requirements

- In the survey, you categorized several functional requirements as must, should, or could-have features. Can you walk me through your reasoning behind this overall prioritization?
- Do you feel this prioritization would hold across most clients and contexts, or does it depend heavily on the specific company, project, or sub-sector?
- If a decision-support tool integrated the must/should/could-have features identified in literature, would it be useful for your work?
 - Are any features missing?
- Must-have: The tool provides insight into the financial risks and returns of Twin Transition investments
 - How do you currently evaluate the economic viability of Twin Transition investments?
 - What time horizons or forecasting periods are most useful for you?
 - Would you want these insights broken down per project, business unit, or company-wide?
- Must-have: The tool maps the positive and negative sustainability impacts of digital technologies
 - How do you currently assess or map these impacts, if at all?
 - What challenges do you face when trying to track negative impacts of digitalization (e.g. energy use, social disruption)?
- Should-have: The tool maps the next steps of the sustainability transition specific to Dutch high-tech manufacturers
 - What type of guidance or roadmap would you expect from such a tool?
 - Would you want these steps to be maturity-based or thematic (e.g. energy, circularity)?
- Should-have: The tool is adaptive to the specific context of a high-tech manufacturing company
 - What aspects of a company’s context should the tool take into account (e.g. size, digital maturity, product type)?
 - How important is customizability in your strategic tools?
- Should-have: The tool enables quantification of Twin Transition-related decisions and their long-term effects
 - Which Twin Transition decisions do you think are most critical to quantify?
 - Do you currently use models or assumptions to estimate long-term outcomes?

Structural requirements

- Which characteristics would make an ideal decision-support tool for your work?
 - Structured decision pathway
 - Quantitative assessment support
 - Flexibility to use for different company contexts
 - Ease of use
 - Comprehensiveness
- You ranked several structural features as must, should, or could-have. Can you share your reasoning behind these choices?
 - What makes a structural element essential versus just helpful?
 - Do these priorities reflect what would work best for your workflow, or what your clients expect and respond to?
- Must-have: The tool uses cost-benefit analysis

- Which elements are essential in a cost-benefit analysis for it to be helpful in your decision-making?
- What barriers exist to applying CBA in your current work?
- Should-have: The tool employs standardized KPIs to compare technologies' impact
 - Do you currently work with sustainability KPIs? If so, which ones?
 - Would industry-wide standard KPIs be valuable to you?
 - How should the tool deal with trade-offs between different KPIs (e.g. energy savings vs. resource use)?
- Should-have: The tool incorporates digital and sustainability maturity models
 - What dimensions should such a model include?
 - Should maturity be assessed at the site, department, or company level?
- Should-have: The tool uses a weighting system to include user priorities
 - Would you want to assign weights to different goals (e.g. cost vs. sustainability)?
- Could-have: The tool employs LCA to assess the direct and indirect sustainability impacts
 - Do you currently use LCA (Life Cycle Assessment) in your sustainability planning?
 - Would integrating LCA into a decision-support tool make it more credible or transparent for you?
 - At which stage of decision-making would LCA results be most useful?
- Won't-have: The tool uses open areas that companies can fill in with their own input
 - Why are open areas not useful?
 - Should there be guidance or templates for filling in content to make this feature useful?

4. Closing question

1. Is there anything you would still like to mention about what we have discussed today?

C.2.3. Interview summaries

Summary interviewee P1

When asked about how digital and sustainability strategies are currently developed for clients, P1 explains that these topics are still often handled in an ad hoc, deal-specific way. "In very large deals... you try to position yourself. Then sustainability or digitalization is an excellent way to differentiate yourself." However, for smaller projects, these aspects often remain underdeveloped or lean due to budget limitations and a lack of urgency from clients.

At present, there is no structured or standardized tool in use within P1's teams for the formulation of integrated digital and sustainable strategies. As a strategic tool to shape value propositions during business development (and measure value during delivery) P1 is internally using the "360 Value Overview". The set-up of this tool is loosely structured by providing value categories, and in practice mainly qualitative value metrics are being defined.

"What we do have is, for example, a 360 Value Overview... It's less of a fixed structure and more a set of value categories and examples of value metrics which might be relevant." P1 highlights a key reason for this: the foundational data needed to populate such a tool isn't always readily available. P1 emphasizes the need for a structured base of implementation knowledge that could serve as input for strategic decision-making. "So you can't just fill a tool like that. There really ought to be a structural foundation."

P1 sees significant potential for a tool that can support both Accenture and its clients, particularly if it helps clients compare strategic options and vendors based on their own client context. From P1's perspective, such a tool would be even more useful on the client side, especially during the RFP process. "The client context is super relevant to make it really specific. Then you can truly compare apples to apples."

P1 stresses that decisions are more powerful when they're made with quantified information, a theme P1 returns to repeatedly. While qualitative insights have their place, companies are far more likely to act when the benefits are tangible and clearly linked to financial outcomes. "There has to be a business case underneath or a clear quantified link to strategic business objectives... visible on the bottom line, otherwise very little tends to happen."

This leads to the first must-have requirement: The decision-support tool must provide cost-benefit analysis for digital technologies, especially showing ESG impact in quantified terms. P1 suggests a typical investment horizon of 3-4 years for such decisions.

Closely linked is the second must: The decision-support tool must assess both positive and negative impacts of digital tools on sustainability. Technologies like IoT can deliver efficiency, but they also consume energy. Both sides of the impact must be visible to enable balanced decisions. "In my opinion, you need to include both in order to form a well-balanced judgment."

In a similar way, P1 supports the idea of using standardized, quantifiable indicators to measure sustainability across economic, environmental, and social dimensions, but sees this more as a second phase in tool development. "I would definitely want to have that, but I see it as a next step." Thus, standardized sustainability indicators are a should-have, valuable for comparison and benchmarking but not immediately essential.

They also emphasize that a tool should allow for flexibility in how those dimensions are prioritized. "You really need to be able to compare apples to apples... with a customized matrix." So, the decision-support tool must be flexible for company specifications, including the ability to customize weights and KPIs. Although P1 doesn't work directly with maturity models, P1 sees the value in using them to determine a company's current position and future direction in the Twin Transition. P1 distinguishes between digital maturity (often part of the value proposition) and sustainability maturity (more often linked to reporting and compliance). "You should be able to indicate: where am I now, and how do I get there?" Therefore, the decision-support tool must have clear maturity stages to map current status and desired progress.

They see benchmarking internal progress as very useful, especially for building a narrative and showing internal stakeholders what the change journey looks like. "That way, they can more objectively assess how their current situation transitions into a future one." So, the decision-support tool must support internal benchmarking. When it comes to the look and feel of the tool, P1 is pragmatic. It matters less what the tool looks like and more how it functions. P1 recommends aligning it with familiar structures, like ESG or CSRD, but defers the final choice to what's most relevant to the client. "For me, it's about how the tool works, not what it looks like... I would just choose the most relevant framework." So, visual presentation and alignment with existing frameworks are could-haves.

They are skeptical about including skill gap detection or training components in the tool. P1 sees this as outside the strategic scope, and better suited to other processes. "I would keep the tool focused on competencies and not make it too broad... There are other methods for that." Thus, training and upskilling recommendations are a won't-have.

Similarly, P1 is clear that compliance and reporting are not the focus of the tool. Many clients already use SAP or other systems for that. While there may be touchpoints, the decision-support tool should focus on supporting strategic choices, not tracking regulatory metrics. "I would really keep compliance separate from the core question: how do I make the best choice when undergoing change?" They also do not see value in implementing a stage-gate approach in the tool. In practice, clients make a decision and proceed, there's rarely time to pause between gates. "For me, it's not a stage-gate process with multiple gates. You make a decision, and then you execute it."

At the end of the interview, P1 reiterates that there is a real opportunity for such a tool, especially if it raises awareness of sustainability and brings structured insights into conversations that are often vague or politically driven. The tool should help decision-makers understand both financial and non-financial impacts of strategic choices. "It then becomes almost an awareness tool: you know what you're getting into when you make changes... This is the business case, and this is the sustainable impact." By enabling structured, contextualized comparisons and surfacing trade-offs clearly, the decision-support tool can serve as a bridge between IT and business, as well as between strategic goals and real operational choices. "When you implement changes in processes or systems, you use the tool to determine: What are my options, and how do I implement them in the most sustainable way?"

They close by affirming that, if the tool captures the elements discussed, it would be of great use to companies, especially those who currently lack structure or momentum in their sustainability efforts. "Many companies aren't doing anything with this right now, but if you set clear goals, a tool can help you make better decisions."

Summary interviewee P2

P2 describes that digital strategy typically dominates discussions, but in high-tech industries, sustainability is increasingly recognized as strategically valuable. “We always do look at it from a digital angle... But ultimately it’s about: what are the company’s values? How can the transition create value in and of itself?” Strategy is framed around creating value.

In terms of tooling, P2 confirms there are calculators and assessment tools used (e.g., footprint calculators), but these are often used for client-specific conversations rather than as part of a standardized approach. A “talking piece” tool is considered useful: “It’s helpful not to show up with a blank page, but with something that shows: this is how we look at it.” P2 emphasizes the need for co-creation and modularity, allowing a tool to be adapted to the client’s specific priorities, thus, the tool must be flexible for company specifications. “We often use best practices from the industry. That is always a good starting point. And then you can look together with the customer: what do you recognize or not? Then you cross things out or challenge them.”

P2 emphasizes that clients respond most strongly to cost-benefit insights, especially when tangible benefits are clearly quantified. P2 notes that quantification can take many forms, from direct financials to indirect proxies such as employee satisfaction or risk mitigation, but there must be a quantitative base: “Ultimately, yes. Sometimes we combine both: things you can express directly in money, and things you price indirectly.” Hence, the tool must be quantified as much as possible, including for progress and impact across sustainability dimensions.

This leads into the need for structured visualizations of trade-offs. “If you go left, costs go up but your sustainability score improves. Or the other way around: costs go down, but sustainability drops.” This underscores the requirement that the tool must give insight into trade-offs between economic, environmental, and social impacts.

P2 is an advocate for standardized KPIs to enable benchmarking, both internally and externally. “It’s easy to think internally: we’re doing well. But if you then compare to an industry standard, it might turn out you’re falling behind.” Therefore, the tool must include KPI standardization to benchmark against peers and must also support internal benchmarking of progress over time. In terms of structure, P2 recommends a hierarchical KPI framework, starting with a few key indicators and branching out: “I would say: start with five, and usually you end up with ten to twelve... You have primary KPIs... and below those there can be additional KPIs.”

The idea of multi-criteria decision analysis (MCDA) resonates with P2, especially when it supports weighting across sustainability priorities: “You might end up somewhere in the middle on average, depending on the company’s priorities.” This supports the concept that the tool could incorporate weighted scoring models based on client-defined priorities.

P2 also advocates for a stage-gate model to provide milestones and track progress over time. “For example, through a structured approach with milestones... sustainability also isn’t something you do just once.” Thus, the tool should include clear milestones between maturity stages, and must have clear maturity stages to map progress and status.

P2 highlights the importance of making sustainability dimension scores visible, preferably in a format that can show the impact of specific decisions across ESG dimensions. “You could then say: the E-score goes up, but the S-score drops... That way, you create an average score aligned with their strategic priorities.” This visual representation of TBL (Triple Bottom Line) dimensions is a should-have, particularly if it allows clients to weigh impacts differently depending on their goals.

In terms of presentation, P2 envisions a clickable overview showing summary scores per stage and per ESG dimension, which then expands into sub-projects and underlying actions. This layered structure supports both high-level insight and drill-down detail.

The role of the tool as a client-side decision-making support tool is emphasized: “You can license it from us... so they can use it themselves. Then they can apply it internally and determine: who offers me the best digital solution, and what is the sustainability impact of that?” Thus, the tool could be used by clients to evaluate vendor propositions.

Finally, P2 warns against excessive complexity: “Then you risk analysis paralysis... Clients also often

want something that fits their specific situation.” Hence, usability and focus are important, concrete actions to improve performance are a could-have, but only if they don’t overwhelm the tool’s core value.

Summary interviewee P3

P3 describes that digital and sustainability strategies are always shaped by the specific context of the client. Some clients proactively initiate digitalization to improve production performance, for example, by reducing costs of non-quality, while others have not yet developed a clear understanding of how digital and sustainability transitions can benefit their business. In either case, clients typically seek guidance on which partners and capabilities are required to implement such changes. “Clients may already have a specific question... But it could also be that they don’t yet have this clearly on their radar.”

Strategy formulation involves determining whether the client can execute the transition internally, or whether they need technology vendors or system implementation partners to help. These decisions are influenced by the client’s network and their prior experience with similar projects. P3’s team is often brought in during early conversations, particularly when the client is evaluating proposals or considering transformation initiatives.

P3 sees clear value in a decision-support tool that can aid both in the preparation phase and as part of the ongoing process of digital and sustainable transformation. Clients want to understand how such a tool works before engaging, particularly in the context of vendor selection or proposal assessment. “So to your question: is it mainly for the preparation phase? Yes, always during preparation... Even if it’s a tool for day-to-day use, they still want to see how it works upfront.” Thus, the tool should support both preparatory and active phases of the transition, this is considered a should-have.

The most critical functionality, according to P3, is the ability to evaluate the cost-benefit of digitalization initiatives with respect to sustainability. The tool must make it clear how the investment compares to both the economic returns and the environmental/social benefits. “You want to know: what does the cost-benefit look like, how does the investment compare to the returns? That’s crucial in any business decision.” For this reason, the tool must provide a business case view that incorporates both digital and sustainability aspects.

This evaluation should include not just up-front investment costs, but also ongoing operational costs, such as software licenses, cloud usage, and training. P3 indicates a reasonable evaluation horizon is between one and three years: “You’re not done with just the initial investment... run-costs, training, licenses... and cloud consumption. You have to take all of that into account for 3-5 years.” P3 also connects cost-benefit analysis to the risk of non-compliance: “For example, look at the risks of fines, lawsuits or other consequences. It just happens if you do nothing.”

A second must-have requirement is that the tool enables evaluation of both positive and negative effects of digitalization on sustainability. Clients need to understand trade-offs. “When you do an evaluation, you look at both sides. You don’t know in advance what will turn out positive or negative.”

In line with this, P3 emphasizes the importance of evaluating sustainability impacts across all three ESG dimensions: economic, environmental, and social. While not everything can be expressed in financial terms, it is still important to define clear KPIs per domain. “You can’t express everything in financial terms... You need standardized KPIs for each sustainability aspect. It’s helpful to align with what’s already known in the market.” Therefore, the tool must quantify key dimensions where possible, and could include qualitative aspects as secondary insights when monetization is not feasible.

At the same time, P3 cautions that companies often select only certain ESG goals based on relevance to their business. For example, water usage KPIs may be irrelevant for some firms. Thus, the tool must allow for modularity and flexibility in which sustainability goals are prioritized, depending on company context. “Companies usually select a few Sustainable Development Goals to focus on... So yes, some flexibility is needed.”

P3 is also asked whether the tool should be specific to the medtech sector or more broadly applicable across high-tech. They stress that differences in regulation and manufacturing systems between companies that work in the semiconductor industry and a medtech device manufacturer make this difficult. “[A semiconductor company] makes something very different from a diabetes pump... The systems and production processes differ greatly.” This suggests that industry-specific adaptations could

be a should-have, especially where sector regulations strongly shape how sustainability is addressed.

P3 acknowledges that regulatory pressure is growing, particularly through instruments like the CSRD. Companies like Philips have taken a leading role in sustainability reporting, not just for compliance but also as a strategic differentiator in client tenders.

“So you simply need to be able to report on that and play a leading role in it.” While this implies that regulatory context is important, reporting itself is not seen as a core functionality of the tool, a won’t-have.

The inclusion of skills and capabilities in the tool, such as identifying workforce gaps, is viewed by P3 as valuable, but not essential to the core purpose of the tool. Implementation planning, including skills, typically follows strategy formation. “Training and upskilling can’t be an afterthought... but keep it manageable for yourself. I see this more as a nice to have.” Thus, highlighting skills needed for next steps is a could-have, but only if it doesn’t complicate the tool excessively.

In terms of structure, P3 expresses no preference for a specific format but suggests avoiding Excel in favor of a more user-friendly interface, potentially web-based. “Maybe something with a more user-friendly interface... but then how do you process all the data points?”

The underlying concern is how to manage data input and complexity without creating a “black box” tool. This underscores the importance of usability and clarity as design principles, even if not formal requirements.

Summary interviewee P4

P4 emphasizes that sustainability is not a standalone process but rather an integrated aspect of broader product development workflows. In PLM-driven environments, strategies such as “Sustainable by Design” are employed to embed sustainability checks within existing roles and systems, particularly for New Product Development (NPD). “Sustainability is therefore an aspect within a process, not the process itself.”

This process-driven view underscores that sustainability decisions must align with the decision rights of each stakeholder. For example, a packaging developer can decide on material and weight but not on the manufacturing location. “Each department has its own decision rights... within PLM, you need to look at the decisions a developer can actually make.” Consequently, a cross-functional tool would need to respect these boundaries.

P4 describes that in current practice, business process design is often without any tool, mapping workflows and decision points before sustainability is added. This means that sustainability criteria emerge as constraints or evaluation points later in the process, not as the central driver. “There’s usually no separate end-to-end ‘sustainable design.’ They are steps within existing processes.”

Tools such as digital maturity models are used in some domains, including PLM, but are not yet widespread for sustainability. P4 sees potential in adding sustainability layers to such models, using frameworks like the Sustainability Value Chain to zoom in from strategy down to department-level actions. “You start with an overarching strategy... then you look at what that means for a department like R&D.”

However, there is a recurring concern: companies often resist adopting new tools unless clearly integrated into existing environments. “Most users aren’t exactly waiting for yet another tool.” This suggests that the tool should integrate with existing tools and workflows, a should-have, or there is a risk of non-adoption.

P4 highlights a specific pain point: sustainability data in PLM is often unreliable or inconsistently updated. A consumer product manufacturer, for instance, used additional sustainability tables in PLM, but these were not maintained, leading to a drop in usage. “As a result, you see that the use of sustainability data in PLM is declining.”

A separate, centralized system might improve usability if it acts as a single source of truth for sustainability data, especially during the decision-making phase, where design alternatives are evaluated. “You want to know: I have four alternatives, which one should I choose?”

When it comes to sustainability in production processes, P4 views change as difficult due to legacy infrastructure. Even when digitalization improves efficiency, most changes are economically motivated, and environmental gains are secondary. “The factory is already there... The investment costs to modify a factory are often very high.” Thus, the tool could propose actions based on practical constraints (e.g., low-budget vs. high-budget options).

Quantification emerges as a critical theme. P4 suggests that even though certain sustainability aspects (like water or biodiversity) are hard to quantify, energy consumption, and its CO₂-equivalent, remains the most tangible indicator. “That does reduce sustainability to just energy, but it’s often the most tangible aspect.”

So, quantification of sustainability impacts (especially CO₂ and energy) is a must-have, even if the economic valuation is simplified. P4 also outlines a client’s use of three primary indicators: CO₂ impact, recyclability (RRI), and water usage, across the product lifecycle. Thus, flexibility in the tool to align with the sustainability priorities of a client is a must-have.

Finally, P4 supports benchmarking both internally and externally. Internally, the tool should enable tracking of current vs. historical performance. Externally, companies within the same subsector should compare themselves to peers, but lack trustworthy data. “What many companies lack is the ability to compare... That insight would be a valuable addition to your tool.”

Summary interviewee P5

The conversation began with a discussion of how strategies are formulated for digitalization and sustainability. P5 explains that for digital transformation projects, Accenture has “off-the-shelf” materials and methodologies, such as “how do you carry out a transformation, how do you build a digital roadmap.” However, the integration of sustainability is limited into these strategic toolkits. It is still treated as a separate capability within the organization, and “it’s still difficult to properly connect that to the client’s question.”

According to P5, clients often treat sustainability as an isolated topic: “You rarely get a functional question in which sustainability is integrated.” Instead, questions from sustainability teams are handled separately from functional questions, making integration difficult. This is reinforced by the perception that sustainability is something “fluffy,” which diminishes its legitimacy in the eyes of many stakeholders.

To address this, P5 identifies a key requirement for the tool to make sustainability “tangible,” concrete and embedded in daily operations. Demonstration capabilities of the tool are seen as critical: “It helps enormously if you can show a demo during a client meeting... that makes it clear what we can actually implement.”

A recurring theme throughout the conversation is the need for structured, fact-based decision-making. P5 emphasizes the importance of helping clients make trade-offs: “When do you consciously invest a bit more money to benefit from it over the next 20 to 30 years?” Therefore, the tool must give insight into trade-offs of next steps in digital, including both positive vs. negative and economic vs. environmental vs. social aspects.

To make these trade-offs more relatable, P5 shares a concrete example: a Dutch high-tech manufacturer moved from air to boat shipments to reduce emissions. But such decisions come with cost, speed, and operational impact. The tool should therefore support business case assessment, including “year-on-year return,” and a longer horizon is a clear must. P5 emphasizes that high-tech firms struggle with long-term thinking: “2050 is way too far ahead. Even 2030 already feels far to them.” This suggests the tool could connect short- and long-term planning, but within a 3-5 year horizon.

To enable such analysis, P5 confirms the need for quantification: “The first thing [the clients] ask is: what’s the KPI? How do you make this fact-based?” Clients expect quantified KPIs across multiple layers: strategic (“if something is red”), tactical, and operational (e.g., “how much emissions resulted from that?”). At the same time, qualitative context should complement quantification: “Some elements can be quantified, others less so, but that’s how you get that layering.” Thus, qualitative insights are a useful sidenote.

This leads to the topic of benchmarking. Benchmarking with industry peers is a sensitive issue in high-

tech. Companies see themselves as unique and resist comparisons outside their niche. Still, P5 suggests that benchmarking within the sector, e.g., other true high-tech peers within the same sub-sector, could create a sense of urgency: “That’s when they truly feel mirrored.” When discussing flexibility, P5 supports allowing clients to prioritize dimensions within boundaries: “The tool should provide boundary conditions... But within those, you need to offer flexibility.” This flexibility, coupled with clear structure, supports effective implementation.

In terms of structural design, P5 confirms the need for a clear maturity model: “You’re either still completely at the beginning, or already a bit further along.” Maturity curves or visualizations of stages would help companies see “which logical next steps go with that.” The tool must be designed to show trade-offs visually, balancing cost, sustainability, and efficiency: “I see it as a triangle in which you have to balance three pillars.” P5 suggests that a spider graph or similar overview could visualize progress and opportunities: “one picture that captures the entire picture.”

A guiding framework such as the People, Process, Technology model is also confirmed by P5 as useful: “It’s the language companies understand.”

Finally, when asked about training and skills, P5 is clear that identifying skill gaps is not a priority at this stage: “There’s little point in already starting training or identifying skill gaps at this stage.”

D

Phase 3 materials

D.1. Foundational model

Table D.1: Fit of requirements with Accenture Industry Sustainability Maturity Model

Requirement type	Requirement	Fit with Accenture Industry Sustainability Maturity Model
Functional	Integrate priorities from the company (F1)	The dashboard aggregates and displays current vs. target ESG scores in one graph.
Functional	Progress from different maturity stages (F2)	The model has four maturity levels, allowing different activities to show varying maturity.
Functional	Quantifies maturity stages for positioning and tracking (F3)	Four levels (0–1.1, 1.2–2.4, 2.5–3.7, 3.8–5.0) translate survey scores (based on a 5-point Likert scale) into maturity positions.
Functional	Shows trade-offs between economic and sustainability (F4)	Not included, but could be added to the “next steps” component.
Functional	Shows trade-offs between positive and negative sustainability (F5)	Not included, but could be added to the “next steps” component.
Functional	Benchmarking of company’s own progress (F6)	Visual comparison between current and target ESG scores at both detailed and aggregated levels.
Functional	Benchmarking of company’s progress against proxy-peer companies (F7)	Not currently included, but could be added by comparing company scores against selected peer benchmarks.
Functional	Assesses total cost of ownership ROI for 3–5 years (F8)	Not included, but could be integrated into the “next steps” component.
Structural	Clear core message (S1)	Provides a strong core message by showing the overall sustainability score and breaking it down into ESG components and a people/policy/process diagram.
Structural	Clear maturity stages specifically for the Dutch high-tech manufacturing sector (S2, S5)	Uses four stages: not implemented, partially implemented, largely implemented, fully implemented. Could be tailored to Dutch high-tech specifics.
Structural	Uses MCDA to customize priorities (S3)	Does not use MCDA; currently assumes equal weighting across impacts, but this could be adjusted.
Structural	Visualizes scores (current, progress, goal) per sustainability dimension (S6)	ESG dashboard shows detailed maturity levels for current and target ESG scores across subcomponents.
Structural	Visualizes score of current and target maturity (S7)	Dashboard provides side-by-side visual comparison of current vs. target ESG scores.
Contextual	Facilitation of strategic discussions of Twin Transition planning (C1)	Designed to support strategic discussions for improving operational sustainability; could be adapted to guide Twin Transition planning.

Requirement type	Requirement	Fit with Accenture Industry Sustainability Maturity Model
Contextual	Usable across different levels of company Twin Transition maturity (C2)	Applicable for companies at both beginner and advanced sustainability maturity levels.

D.2. Maturity model development: sub dimension identification

D.2.1. CSRD & ESRS analysis for Dutch high-tech manufacturing relevance

The EU CSRD requires high-tech manufacturers in the Netherlands to report on Environmental, Social, and Governance (ESG) impacts of their in-factory operations, using the ESRS. Below the key ESG impact areas for subsectors including semiconductor fabrication, medical device production, precision machinery, and aerospace manufacturing are analyzed. Each impact is linked to the specific mandatory ESRS disclosure requirement (e.g. ESRS E1-5) under the CSRD framework. The focus is on direct factory operations (energy use, process emissions, occupational health, on-site governance, etc.), and excludes purely upstream or downstream impacts. All ESG impacts are based on the review of the European Sustainability Reporting Standards as detailed in European Commission (2023a).

Environmental impacts

High-tech manufacturing facilities must manage several environmental impacts of their operations under the CSRD. The ESRS environmental standards E1–E5 define mandatory disclosures on climate, pollution, water, biodiversity, and resource use. For each impact area, companies need to report their policies, action plans, targets, and quantitative performance as required by the ESRS.

Energy use and GHG emissions

High-tech manufacturing is energy-intensive, leading to significant climate impacts. All subsectors must report energy consumption and their energy mix (renewables vs. non-renewables) under ESRS E1-5. For example, semiconductor fabrication plants have enormous electricity demand to maintain ultra-clean cleanroom environments and operate equipment (lithography lasers, vacuum pumps, etc.), far exceeding typical manufacturing energy intensity. Precision machinery assembly (e.g. building lithography machines) also uses cleanrooms (though on a smaller scale) requiring constant climate control. The resulting greenhouse gas emissions (from purchased electricity or on-site fuel combustion) are disclosed via ESRS E1-6, including Scope 1 (direct), Scope 2 (energy indirect), and Scope 3 if material. Semiconductors in particular must report any process-related GHGs like perfluorinated compounds (PFCs) and sulfur hexafluoride used in etching and chamber cleaning, these are potent greenhouse gases contributing to climate change and are counted in Scope 1 emissions. Other subsectors mainly report CO₂ from energy use (e.g. natural gas for facility heating or process heat in aerospace autoclaves). All high-tech firms must have climate mitigation plans (e.g. efficiency projects, green energy procurement) and possibly targets for emissions reduction per ESRS E1-1 to E1-4, but the core impact metrics are energy use and GHG emissions (which are considered material for virtually any manufacturing company).

Air, water and soil pollution

High-tech manufacturing processes can emit pollutants that affect local air and water quality. ESRS E2-4 requires disclosure of pollutants released through the company's own operations to air, water, or soil. In all subsectors, manufacturers must manage emissions of volatile organic compounds (VOCs), particulates, and other regulated substances. For example, aerospace and precision machinery plants often include painting/coating, metalworking or welding. These are activities that emit VOCs, particulates, or metal fumes to air if not filtered. Medical device plants may use sterilization gases like ethylene oxide (a hazardous air pollutant) or solvents for cleaning, which must be controlled. Semiconductor fabs handle acids, solvents, and gases; while much is in closed systems, they can emit acidic fumes or greenhouse gases not fully abated. They also produce water pollutants in their wastewater (e.g. fluoride, heavy metals from etchants) that require on-site treatment before discharge. Companies must report emissions data such as NO_x, SO_x, VOCs to air, chemical oxygen demand (COD) or other water quality metrics if material. Soil contamination is less typical in these clean industries, but any incidents (spills of chemicals, etc.) would fall under this as well.

Use of hazardous substances

High-tech manufacturing often involves substances of concern, which are chemicals that can impact health or hinder circular economy if not managed properly. Under ESRS E2-5, companies must disclose their use of substances of concern and substances of very high concern (SVHC) as defined by EU chemicals law. This means identifying any hazardous chemicals produced or used in the factory. For instance, semiconductor manufacturers use strong acids (like hydrofluoric acid), bases, photoresists containing solvents, and potentially fluorinated compounds (some of which are PFAS chemicals). These should be reported if they appear on concern lists. Aerospace manufacturers might use paints and primers containing chrome VI or other heavy metals (though largely phased out, any remaining use must be tracked), or composite manufacturing resins/adhesives that are harmful if not handled properly. Medical device production may involve biocidal substances or sterilants (ethylene oxide, formaldehyde) that are hazardous. ESRS E2-5 disclosure prompts companies to report how much of these substances are used or produced, and how they are managed, to mitigate environmental and health impacts. The goal is to ensure transparency about toxic substances at the facility level and encourage substitution with safer alternatives.

Water usage and effluents

Water is a critical resource in many high-tech production processes. ESRS E3-4 mandates disclosure of water consumption associated with the company's operations. Semiconductor fabrication is particularly water-intensive, fabs consume vast amounts of ultra-pure water for wafer processing (cleaning, rinsing, chemical baths) and require continuous supply. For example, a single large fab can use millions of liters of water per day, making water availability and recycling a key operational concern. This subsector will need to report total water withdrawal and consumption, and likely water recycling rates, given the materiality. Other subsectors have moderate water use: aerospace machining and surface treatment lines (anodizing, plating) use water for rinsing, precision machinery assembly uses water mainly for coolant in machining and some cleaning, medical device plants use water for cleaning and sterilization processes. Companies must disclose not only how much water they use, but also any water stress considerations if their factories are in water-scarce areas (for the Netherlands, water stress is generally low, but efficient use is still expected). Wastewater discharges fall under pollution (E2-4) for water quality, but E3-4 focuses on quantity used. Firms should show efforts to minimize water consumption (through recycling ultra-pure water in fabs, for instance) as part of their environmental targets.

Biodiversity and land use

While not a primary impact for most high-tech manufacturing sites, the ESRS requires consideration of biodiversity effects. ESRS E4-5 calls for metrics on the company's impacts on biodiversity and ecosystems. In practice, high-tech factories are usually located in industrial zones or business parks (e.g. Brainport Eindhoven for electronics, aerospace industrial estates, etc.), so direct impacts on biodiversity may be limited. However, companies must assess if any operations are near protected areas or if their activities affect local ecosystems. For example, if an aerospace plant does engine testing that creates significant noise, it could disturb wildlife in the vicinity (a potential biodiversity impact). Or if a factory's footprint involved converting greenfield land, there could be habitat loss to report. Under ESRS E4, companies disclose any such impacts and their mitigation efforts. Even if the conclusion is that biodiversity impact is not material (common for urban/industrial locations), the CSRD double materiality principle requires the assessment to be done.

Resource consumption (materials)

Apart from energy and water, manufacturers must report on raw material use in their operations. ESRS E5-4 addresses resource inflows, requiring disclosure of the materials used in production. High-tech products often rely on specialty materials: semiconductor fabs use silicon wafers, dopant chemicals, precious metals for contacts, aerospace manufacturing consumes metals like aluminum, titanium, composites (carbon fiber and resins), precision machinery uses high-grade steel, optics (glass), and electronics, medical device production uses plastics, biomedical materials, etc. Companies need to quantify the total weight of materials used, including critical raw materials and rare earth elements if applicable. This ties into circular economy principles, the standard specifically asks for the share of recycled or renewable materials used. All high-tech subsectors are encouraged to improve material efficiency (designing smaller, lighter components, using recycled metals, etc.). By disclosing resource

inflows, manufacturers give transparency on their consumption of finite resources and can demonstrate improvements (like increasing recycled content in products or reducing scrap).

Waste and circularity

All manufacturing processes generate waste, so companies must report resource outflows under ESRS E5-5, including waste generation and how it is managed. This covers both hazardous and non-hazardous waste streams. Under ESRS E5, companies need to disclose not only the amounts of waste but also how much is reused, recycled, or sent to landfill/incineration. This reflects their contribution to the circular economy. For example, an aerospace firm should report the percentage of metal scrap that is recycled back into the material supply chain. Additionally, ESRS E5-5 prompts disclosure of any strategies to design products for circularity (durability, repairability), which, while more related to product design (downstream use phase), can influence in-factory processes (e.g. separating waste for recycling). All subsectors will address waste management as a direct operational impact, ensuring compliance with waste regulations and pursuing waste reduction targets if material.

Social impacts

The social dimension of sustainability under CSRD covers the company's impacts on people. Primarily its own workforce for high-tech manufacturers (ESRS S1), but also potentially workers in the supply chain (ESRS S2), affected communities (ESRS S3), and consumers (ESRS S4). For in-factory operations, the focus is on the company's own employees and on-site workers. High-tech manufacturing in the Netherlands involves highly skilled labor and safe working environments, but there are still important social impact areas to monitor and report.

Worker engagement and representation

Dutch high-tech firms typically have structured worker representation, such as works councils (*onderneemingsraad*) and often labor union presence, ensuring dialogue between employees and management. ESRS S1-8 requires disclosure of the percentage of employees covered by collective bargaining agreements and the nature of social dialogue. In practice, many large tech manufacturers in NL have collective labor agreements or at least active works councils that cover a broad range of workforce issues. Companies will report metrics like what portion of the workforce is under collective bargaining and describe how they engage with employee representatives. This is a general impact across all subsectors, whether it's an electronics firm or an aerospace parts manufacturer, worker voice and consultation on workplace conditions are a social performance aspect. Strong social dialogue can be seen as a positive impact (upholding labor rights) and helps address any grievances proactively (which also links to S1-3 on grievance mechanisms).

Diversity and inclusion

High-tech manufacturing has traditionally been male-dominated, especially in engineering and production roles, so improving diversity (gender, age, ethnicity, disability inclusion) is a key social sustainability theme. Under ESRS S1-9, companies must report diversity metrics such as gender distribution in management and age distribution of employees. Additionally, ESRS S1-12 specifically calls for information on employment of persons with disabilities. They may also disclose other aspects of diversity (though ESRS focuses on certain metrics like gender and age). The impact here is ensuring equal opportunity and a diverse workforce, which can enhance innovation and social equity. Companies will likely set internal targets to increase diversity, and CSRD reporting will track progress (e.g. % of female engineers or leadership).

Fair wages and working conditions

ESRS S1-10 requires disclosure of whether employees are paid an "adequate wage" (living wage) in each country, and what percentage are not if any. Additionally, ESRS S1-11 covers social protection, benefits like pensions and health insurance, ensuring employees have basic social security coverage. Since Dutch law mandates strong social protections, companies will likely report that nearly 100% of workers have pension plans, etc. Another aspect of working conditions is hours and work-life balance. The impact of fair wages and benefits is that the company is not contributing to in-work poverty or inequality. This is uniform across subsectors, all must confirm their factory workers are paid at least a living wage and have requisite benefits.

Training and skills development

Continuous learning is important in high-tech manufacturing, given quick technological evolution and the need for strict quality processes. ESRS S1-13 requires companies to disclose metrics on training provided to employees. This could include the average training hours per employee, or percentage of staff receiving regular upskilling. By reporting training metrics, stakeholders see how the company contributes to employee development. This is applicable across all subsectors, as each relies on skilled labor and must ensure knowledge transfer and growth. Adequate training also ties to safety (trained workers are less likely to cause accidents) and innovation (skilled workers drive process improvements).

Occupational health and safety

Protecting worker health and safety is a critical in-factory impact. ESRS S1-14 mandates disclosure of health and safety metrics. This typically includes the share of the workforce covered by a certified health & safety management system and statistics on workplace incidents, injuries, and lost days. All high-tech subsectors have some H&S risks, though the nature varies: in semiconductor fabs, risks include chemical exposure (acids, gases), cleanroom ergonomics, and potential radiation from equipment. They will also note if 100% of employees are covered by ISO 45001 or similar safety systems (likely yes for large firms). In aerospace manufacturing, risks are more physical, working with heavy parts, cranes, cutting tools, or in confined spaces of aircraft structures, so they track injury rates (e.g. lost-time injury frequency) and safety training participation. Under the CSRD, these companies must publish metrics like number of work-related injuries, fatalities, and near-miss reporting, as well as occupational health initiatives. This level of transparency (reporting even minor incident statistics) ensures they maintain rigorous safety performance.

Work-life balance

The CSRD's social standards also consider how companies support employees' work-life balance. ESRS S1-15 requires disclosure of metrics like the extent employees are entitled to and use family-related leave (maternity/paternity leave, parental leave, etc.). High-tech companies must report how many employees took such leave, which reflects whether workers feel able to utilize these benefits. Additionally, work-life balance could involve flexible working hours or arrangements, but for factory floor jobs, flexibility is limited by shift schedules. The impact here is employee well-being: excessive work hours or inability to take leave would be a negative social impact. By reporting these metrics, companies demonstrate compliance with labor standards and care for employee welfare.

Equal pay and benefits

Ensuring equal pay for equal work, regardless of gender, is another social metric. ESRS S1-16 asks for remuneration metrics, specifically any gender pay gap and the ratio of total compensation. High-tech companies will need to calculate the gender pay gap among their employees. The CSRD reporting will make any pay disparities visible, incentivizing high-tech employers to continue improving representation of women and minorities in higher-level, better-paid roles, thereby narrowing gaps.

Governance impacts

The governance dimension under CSRD focuses on business conduct: how a company's internal governance and behavior uphold ethical standards, compliance, and stakeholder accountability. For in-factory operations, governance impacts relate to the culture and systems that ensure sustainable practices are actually implemented on the ground. The mandatory governance standard ESRS G1 (Business Conduct) defines several disclosure requirements, and high-tech companies must report on these as they apply to their operations. However, most reporting standards are not relevant for the direct manufacturing operations (ESRS G1-3 on anti-corruption and bribery measures, ESRS G1-5 on political engagements and lobbying activities, ESRS G1-6 on fair supply chain payment terms).

Ethical corporate culture and policies

Companies are required to describe their policies on business conduct and how they create a culture of integrity (per ESRS G1-1). This means high-tech manufacturers must report on codes of ethics or conduct that guide behavior of employees and management, including in the manufacturing operations environment. An ethical culture at the factory level might involve regular trainings on the code

of conduct, leadership tone-from-the-top on integrity, and encouragement for employees to speak up (whistleblowing). In fact, protection of whistleblowers is explicitly mentioned as part of business conduct matters. The impact here is ensuring that the company's governance framework actively prevents misconduct and promotes responsible behavior among all staff.

D.2.2. EEIOA results for quantitative sustainability impact assessment

Energy usage

Overview of energy reporting. In line with the CSRD and the ESRS E1, companies must report on their energy performance. This includes disclosure of total energy consumption, the energy mix (differentiating between renewable and non-renewable sources), energy intensity relative to revenue, usage of renewable energy, and exposure to fossil fuels.

Trends over time. Between 2012 and 2015, the Dutch high-tech manufacturing sector recorded a decline in energy use, suggesting early efficiency gains. From 2016 to 2018, energy consumption spiked, largely linked to an increase in production activity and the global semiconductor boom. Between 2019 and 2022, energy use moderately rebounded, with the share of renewables in the energy mix gradually increasing. Energy intensity, measured in terajoules per economic output, improved from 2012 to 2015. Although it worsened slightly in 2020 compared to 2015, it still reflected better efficiency than in 2012.

Comparison to other Dutch manufacturing sectors. In 2020, the Dutch high-tech manufacturing sector consumed approximately 20,680 terajoules (TJ) of gross energy, positioning it among the top five energy-consuming manufacturing sectors in the Netherlands. For comparison, beverage manufacturing consumed 11,663 TJ, fish processing 4,501 TJ, and textile manufacturing 1,864 TJ. The high-tech sector distinguishes itself through relatively high electricity use and a comparatively higher share of renewable energy.

Comparison to supply chain embodied energy use. Direct energy consumption represents only a small part of the sector's total energy footprint. In 2020, while the direct operational energy use was approximately 20,680 TJ, the supply chain embodied energy use was estimated at around 1,052,000 TJ. This means that direct consumption accounted for just about 2% of the total, highlighting the critical role of supply chain emissions in energy-related sustainability assessments.

Air emissions

Emission types in the Dutch high-tech manufacturing sector.

In accordance with the CSRD and the European Sustainability Reporting Standards (ESRS E1 and E2), the Dutch high-tech manufacturing sector is obligated to disclose both greenhouse gas (GHG) emissions and emissions of key air pollutants. The main air emissions reported between 2012 and 2022 include greenhouse gases, specifically carbon dioxide (CO₂), methane (CH₄), nitrous oxide (N₂O), hydrofluorocarbons (HFCs), perfluorocarbons (PFCs), sulphur hexafluoride (SF₆), and nitrogen trifluoride (NF₃), as well as non-GHG air pollutants such as nitrogen oxides (NO_x), sulphur oxides (SO_x), particulate matter (PM₁₀ and PM_{2.5}), non-methane volatile organic compounds (NMVOCs), and ammonia (NH₃).

In terms of absolute quantities, CO₂ is the most dominant emission. However, when adjusted for global warming potential, HFCs emerge as the most significant contributors, followed by CO₂ and PFCs. Nitrous oxide and methane also contribute notably, while emissions of SF₆ remain relatively low and nitrogen trifluoride emissions are virtually zero. For instance, in 2022, direct HFC emissions reached approximately 244 billion kilograms of CO₂-equivalent, which significantly surpassed the 342 million kilograms of direct CO₂ emissions.

Comparison to other Dutch manufacturing sectors.

Relative to other Dutch manufacturing sectors, the Dutch high-tech manufacturing sector stands out for its high emissions of HFCs and PFCs. This reflects the sector's relatively large contribution to emissions from refrigerants and speciality industrial gases. While direct CO₂ emissions are relatively low, the sector reports high emissions of SO_x. In contrast, its contribution to conventional air pollutants such as NO_x, particulate matter, and NH₃ remains limited.

Table D.2: Air emission ranking of the Dutch high-tech manufacturing sector.

Gas	Dutch high-tech manufacturing sector ranking	Conclusion
CO ₂	10 th	Relatively small emitter compared to manufacturers working with raw materials, such as gas, iron, coke, and cement sectors.
CH ₄	6 th	Medium emitter, similar to the office machinery manufacturing sector.
N ₂ O	10 th	Relatively small emitter, especially compared to bio-based material manufacturers.
HFC	8 th	Medium emitter, comparable to rubber, plastic, and tobacco product manufacturers.
PFC	Not in top 10	Small emitter.
SF ₆	Not in top 10	Small emitter.
NO _x	7 th	Small emitter, particularly compared to cement, iron, and steel sectors.
SO _x	3 rd	Medium emitter, higher than expected given the sector profile.
PM ₁₀	5 th	Medium emitter, behind traditional heavy industries.
PM _{2.5}	8 th	Medium emitter, on par with machinery and furniture manufacturers.
NMVOC	2 nd	High emitter, significantly higher than many other sectors such as fabricated metal products.
NF ₃	Not in top 10	Small emitter.
NH ₃	9 th	Relatively small emitter, particularly in comparison to bio-industrial sectors.

Trends over time.

From 2012 to 2022, direct CO₂ emissions declined, dropping from 652 million kilograms to 294 million kilograms. HFC emissions fluctuated considerably, showing peaks in 2017 and 2018. NMVOC emissions remained largely stable throughout the period. Emissions of NF₃ continued to be negligible. A distinct decline in CO₂ and NO_x emissions was observed during the COVID-19 pandemic (2020–2021), with partial recovery in 2022.

Comparison to supply chain embodied emissions.

When comparing direct emissions to those embedded in the supply chain, it becomes evident that indirect emissions dominate the sector's environmental footprint. CO₂ emissions from the supply chain are estimated to be 40 to 50 times greater than direct emissions, while NO_x emissions are approximately 30 times higher. Though HFC and NMVOC emissions are more prominent among direct emissions, significant quantities are also embodied in upstream processes.

Nutrient emissions

Overview of nutrient reporting. Under CSRD and ESRS E2 (Pollution), companies must report significant emissions of pollutants, including nutrient-related emissions such as nitrogen (N) and phosphorus (P), due to their roles in environmental degradation, particularly eutrophication.

Direct nutrient emissions. In 2022, the Dutch high-tech manufacturing sector reported no direct emissions of nitrogen or phosphorus. This confirms that the sector's operations do not contribute to nutrient-related pollution.

Supply chain (embodied) nutrient emissions. While direct emissions are negligible, the sector's supply chain embodies significant nutrient emissions, particularly nitrogen. Phosphorus emissions are also present, though to a lesser extent. These emissions arise mainly from upstream suppliers rather than in-house processes.

Water usage

Types of water considered. In accordance with the CSRD and the ESRS E3, companies are required to report on their interaction with water resources, covering both direct operations and relevant aspects of the supply chain. Water use is typically categorised into green, blue, and grey water. Green water refers to rainwater stored in the soil, mainly relevant to agriculture. Blue water includes surface water and groundwater abstracted for direct use, such as cooling or processing. Grey water represents the volume of freshwater required to dilute pollutants to acceptable water quality standards. For the Dutch

high-tech manufacturing sector, only blue water is of material relevance. Green water is not applicable to the sector's processes, and grey water impacts are indirectly captured through blue water measurements in EXIOBASE.

Trends over time. Water use in the Dutch high-tech manufacturing sector has remained stable over the past three years, with no notable increases or reductions. This stability reflects relatively efficient water management and the sector's limited dependence on water-intensive production processes.

Comparison to other Dutch manufacturing sectors. Compared to the broader Dutch manufacturing sector, the Dutch high-tech manufacturing sector uses substantially less direct water. In terms of blue water use, it ranks higher than sectors such as textiles and apparel but far below water-intensive industries like fish processing.

Table D.3: Water use comparison between the Dutch high-tech manufacturing sector and the manufacturing sector average (2022).

Water type	Dutch high-tech manufacturing sector (2022)	Manufacturing sector NL (2022)
Green water	0 Mm ³	4.58 Mm ³
Blue water	2.24 Mm ³	15.99 Mm ³

Comparison to supply chain embodied water use. Direct operational use of water represents only a minor portion of the Dutch high-tech manufacturing sector's total water footprint. In 2022, direct blue water use accounted for approximately 2.29% of the overall water footprint when considering the full supply chain. This implies that water impacts primarily occur upstream. The estimated supply-chain water use is roughly fifty times larger than direct usage, underscoring the environmental relevance of upstream suppliers.

Raw material usage

Overview of raw material reporting. According to CSRD and ESRS E5 (Resource Use and Circular Economy), companies are required to disclose raw material use, including both renewable and non-renewable resources, use of critical raw materials as defined by the EU, and sourcing strategies that support circularity. No fixed list of materials is mandated; instead, companies must assess materiality based on financial and environmental relevance.

Direct raw material usage. In 2022, the Dutch high-tech manufacturing sector reported zero direct raw material input. This indicates that the sector does not engage in the extraction or initial processing of raw materials. Instead, its operations focus on advanced manufacturing and assembly using pre-processed materials.

Supply chain (embodied) raw material usage. Despite no direct input, the sector's supply chains rely heavily on a variety of raw materials. These include metals such as copper, aluminium, and rare earth elements; non-metallic minerals like specialised clays and sands; and fossil fuel-derived products. Many of these materials are classified as critical by the EU. As a result, raw material-related impacts occur primarily upstream, underscoring the importance of responsible sourcing and supply chain management strategies.

Employment

Overview of reporting. Following the CSRD and the ESRS S1 on social sustainability, companies must report workforce-related indicators, including total employment (headcount and/or full-time equivalent), gender distribution in both general staff and management, training and development efforts, diversity indicators (such as gender, age, and disability), and remuneration and working conditions.

Trends over time. Between 2012 and 2016, the Dutch high-tech manufacturing sector experienced significant employment growth, marked by a 21% increase in total hours worked and a 20% rise in

headcount. After 2018, employment stabilised, followed by a decline during the COVID-19 pandemic. By 2022, the sector had begun to recover, although employment had not yet returned to pre-2018 levels.

Gender representation in the sector improved slightly over the decade. In 2022, women accounted for approximately 23% of the workforce. The share of total hours worked by women increased modestly over time, although the percentage remained lower (at 19.42%) than the headcount share due to fewer average hours worked by women compared to men.

Table D.4: Female participation in the Dutch high-tech manufacturing sector workforce (2012–2022).

Year	Female share of hours	Female share of headcount
2012	17.5%	22.6%
2016	17.4%	21.9%
2020	18.6%	23.4%
2022	19.4%	23.1%

Comparison to other Dutch manufacturing sectors. the Dutch high-tech manufacturing sector is not the largest employer in absolute terms. Regarding gender diversity, it occupies a middle position. It has better female representation than sectors such as chemicals but trails behind sectors like textiles and apparel, where female participation often exceeds 30%.

D.2.3. Review of environmental impacts not included in EXIOBASE

For ESRS numbers E2-5, use of hazardous substances and chemicals of concern, and ESRS number E4-5, no quantitative assessment with EEIOA could be done. EXIOBASE did not contain the impacts for these two categories and other data bases also do not have a focus on waste emissions or biodiversity. Therefore, these environmental impacts were reviewed through qualitative research.

ESRS E2-5: Use of hazardous substances & chemicals

The review of hazardous substances and chemicals released into the air was already covered in the air pollution section (E2-5), so this section focuses specifically on the use of hazardous substances and chemicals in the Dutch high-tech manufacturing sector. For ESRS E2-5, the Dutch high-tech manufacturing sector is notable not for the total volume of materials it processes, but for its intensive and specialized use of hazardous chemicals across several sub-sectors. Semiconductor and electronics manufacturing, for instance, rely heavily on a wide range of hazardous substances, including PFAS-containing chemicals, strong acids, heavy metals, and organic solvents used in lithography, etching, and plating processes (Hess, 2024; Statistics Netherlands (CBS), 2025b). These operations frequently generate chemical waste with high toxicity, including spent process acids, solvents, and chemical residues, despite representing a relatively small share of the nation's overall material throughput (CLO (Environmental Data Compendium), 2020).

The medical technology sub-sector contributes additional chemical risk through its use of sterilization agents such as hydrogen peroxide, along with solvent-based cleaning agents like isopropanol (IPA) and acetone. These substances, while critical to maintaining clinical hygiene standards, result in hazardous waste if not properly managed (United States Environmental Protection Agency, 2004). Furthermore, adhesives and epoxy-based compounds used in medical device assembly can contain solvents that contribute to the sector's chemical hazard profile.

In aerospace manufacturing, the use of solvent-borne and chromate-based primers, corrosion inhibitors, and specialized coatings introduces further complexity. These chemicals, particularly those containing chromium compounds and isocyanates, result in highly toxic liquid waste and sludge (3M Company, 2022). Collectively, these practices illustrate that although the sector's material input and waste volumes are modest compared to construction or food production, the intensity and toxicity of its chemical use significantly elevate its environmental risk profile.

ESRS E4-5: Biodiversity & ecosystems

Key clusters of high-tech manufacturers are located in North Brabant (Brainport Eindhoven with ASML, NXP, Philips, etc.), Twente (high-tech SMEs, Fokker aerospace facilities), and South Holland (marine/aerospace manufacturers around Rotterdam). These are typically located near protected areas or Natura2000

sites. For instance, expansions in Eindhoven lie between forest patches and Natura2000 reserves, creating land-use conflicts (Brainport Eindhoven, 2024). Furthermore, the air pollutants reviewed in the EEIOA, contribute to nitrogen deposition, which threatens sensitive Dutch ecosystems (e.g., heathlands, Natura2000 areas) by acidifying soils and altering plant communities (CLO Environmental Data Compendium, 2024).

Impacts that are less relevant for the Dutch high-tech manufacturing sector are:

1. **Soil contamination:** Spill risks are tightly controlled under Dutch and EU law, and incidents on modern high-tech sites are rare. Legacy soil pollution exists but is not unique to this sector.
2. **Light pollution:** High-tech campuses add some nighttime light, but this is minor compared to urban background levels; mitigation (e.g., LED shielding) is increasingly standard (Institute of Environmental Sciences, Leiden University, 2025).
3. **Noise pollution:** Factory and logistics noise is moderate compared to heavy industry, with limited evidence of local biodiversity impact; Dutch environmental permits set clear boundary noise limits (Kok et al., 2023).

ESRS E5-5: Waste management & circularity

For ESRS E5-5, the Dutch high-tech manufacturing sector is actively engaging in the transition toward a circular economy, yet current implementation remains far from the 2030 policy targets set by national innovation programs (Holland High Tech, 2025). Semiconductor and microelectronics manufacturers are leading the transition with advanced circular business models, including servitization, modular design for disassembly, reuse, and closed-loop recycling systems. These companies are actively increasing the share of recovered materials and implementing take-back programs for high-value components (Hess, 2024). In the aerospace and defence sectors, circular strategies such as refurbishment, remanufacturing, and component recycling are gaining traction, particularly for high-cost parts. However, the complexity of materials and performance requirements poses ongoing challenges to full alignment with ESRS E5-5 disclosure standards. Medtech manufacturers are beginning to adopt circular design principles, emphasizing durability and reusability, but face regulatory barriers related to hygiene and patient safety (United States Environmental Protection Agency, 2004). The sector is still in a transitional phase: while the ambition is high and key innovation projects are in motion, current practices are not yet sufficient to meet circular economy targets without acceleration (Holland High Tech, 2025).

D.2.4. Review of social and governance impacts with MSCI ESG Industry Materiality Map

Just like with EXIOBASE, the MSCI ESG Industry Materiality Map does not have a specific category for the Dutch high-tech manufacturing sector. To address this, the weights for the high-tech contribution to other manufacturing subsectors, as provided in the Velthuisen et al. (2024) report, were used to calculate the relative importance of the social and governance categories in the MSCI ESG Industry Materiality Map for the high-tech sector.

The process began by matching the ESRS social and governance standards to the corresponding social and governance categories in the MSCI ESG Industry Materiality Map. Then, the high-tech sub sectors from the (Velthuisen et al., 2024) report were matched to the relevant industry sub sectors included in the MSCI ESG Industry Materiality Map. For each of these sub sectors, the relevant MSCI categories were reviewed in alignment with the ESRS standards, and the corresponding weight from the MSCI ESG Industry Materiality Map was noted.

Next, these weights were multiplied by the high-tech subsector weights from Velthuisen et al. (2024) to determine the total relative importance of each ESRS social and governance standard for the high-tech manufacturing sector. The individual metrics and total results for the high-tech manufacturing sector are presented in Table D.5.

Based on Table D.5, it can be concluded that the most relevant ESRS standards for the high-tech manufacturing sector include S1-8 (Worker engagement and representation), S1-9 (Diversity and inclusion), S1-13 (Training and skills development), S1-14 (Occupational health & safety), and S1-15 (Work-life balance). Governance is also considered highly important, with the ESRS standard G1-1 (Ethical corporate culture and business conduct) being especially relevant for the high-tech manufacturing sector.

Table D.5: MSCI impact weightings across the subsectors relevant to the high-tech manufacturing sector.

Impact		Elec- tronics	Elec- trical equip- ment	Mach- inery	Vehi- cles	Other trans- port equip- ment	Chemi- cals	Pharma- ceuti- cals	Total high-tech manufac- turing
ESRS	MSCI category / Sub-sector weight	8.0%	12.0%	12.0%	10.0%	15.0%	18.0%	10.0%	
S1-8	Labour management	30.6%	19.7%	0.9%	0.0%	18.0%	0.1%	0.0%	7.6%
S1-9	Human capital development	0.0%	2.1%	20.3%	19.9%	0.0%	0.1%	18.2%	6.5%
S1-10	Pay	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
S1-13	Human capital development	0.0%	2.1%	20.3%	19.9%	0.0%	0.1%	18.2%	6.5%
S1-14	Chemical safety and Health & Safety	7.7%	10.6%	0.0%	0.0%	0.0%	13.4%	0.1%	4.3%
S1-15	Health & Safety	0.0%	0.0%	0.0%	0.0%	16.8%	0.7%	0.0%	2.6%
S1-16	Pay	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
G1-1	Business ethics	52.9%	38.7%	37.6%	47.7%	40.9%	33.0%	33.4%	33.6%

D.2.5. Review of Accenture list of digital manufacturing technologies

Table D.6: Overview of digital technologies and their applications in (high-tech) manufacturing companies.

Digital technology	What it is	Application in (high-tech) manufacturing companies	Core digital manufacturing technologies?
ERP (enterprise resource planning)	Central software to manage finance, inventory, procurement, etc. all related to executing production	Integration of data across departments, to streamline the operational and transactional aspects of manufacturing	Yes
APS (advanced planning and scheduling)	Production planning, scheduling	Optimization of production schedules, efficiency through scenarios	Yes
MES (manufacturing execution system)	Software managing/monitoring production processes on the shopfloor in real time	Track production, integrates with ERP, ensure quality	Yes
SCADA (supervisory control and data acquisition)	System for real-time monitoring (sensors/devices)	Overview of operations, supports predictive maintenance	Yes
PLC (programmable logic controller)	Industrial computer used to automate/control machinery	Execute programmed logic, responds to sensor inputs, automation repetitive tasks	Yes
PLM (product lifecycle management)	Digital platform to manage product lifecycle, facilitates collaboration	Unites R&D, engineering, production, quality teams. Facilitates product development, compliance, and change management	No, PLM mainly supports product design and development, engineering changes, and lifecycle data, before manufacturing begins.
LIMS (laboratory information management system)	Software for managing laboratory/regulatory compliance	Automation of sample testing, batch tracking, lab workflows	No, LIMS is focused on R&D, lab testing, and compliance so it does not directly apply to the manufacturing process itself.

Digital technology	What it is	Application in (high-tech) manufacturing companies	Core digital manufacturing technologies?
HMI (human-machine interface)	Interface letting human operators interact with machines/automation systems	Display real-time data/alarms/control to monitor, control and troubleshoot manufacturing processes	Yes
DCS (distributed control system)	System for controlling complex processes with distributed controllers and centralized monitoring	Automation of continuous processing, increase efficiency and precise control	Yes
Cloud-based storage	Online storage, secure/scalable/remote data access and management	Centralize production data/support collaboration across locations	Yes
IIoT (industrial internet of things)	Network of connected industrial devices/sensors that collect and exchange data	Real-time monitoring, predictive maintenance/quality control	Yes
Edge device	Computing device near production line, processes data close to where it's located	Enables real-time data analysis, reduces latency and improves responsiveness	Yes
Data lake	Central repository that stores large volumes of structured and unstructured data in a raw format	Aggregate data from various sources for analytics, machine learning, data-driven decision-making	Yes
Data store	General term for storing and managing data (includes database, data lake, file system)	Production, quality, sensor data for retrieval by MES, analytics or reporting data	Yes
Data historian	Specialized software for capturing/storing/retrieving time-series data from equipment and processes	Real-time and historical process data for monitoring and trend analysis. Integrates with SCADA/MES/ERP	Yes
Database	Structured data storage system, to store/query/manage data	Support MES/ERP by storing structured data for fast access and analysis	Yes
Industrial connectivity (on-prem)	Software/hardware that connects industrial devices with local (on-premises) environment	Facilitates data exchange between equipment, PLCs, sensors, enterprise systems	Yes
Digital twin	Virtual, real-time replica of a physical asset, connected to its real-world counterpart	Simulate, monitor and optimize production, test process changes, improve product quality	Yes
Closed loop manufacturing	Data from product performance and production is continuously fed back into design and production cycles	Use feedback from IIoT devices and digital twins to adjust manufacturing parameters	No, closed loop manufacturing applies digital twin, APC, MES, and real-time feedback loops to automatically adjust manufacturing processes based on performance data and is therefore a composite application.
Smart quality management	Digital quality management to use real-time data/analytics/automation to monitor and control product quality	Integrates with production systems and operators to provide dashboards, traceability. Supports defect reduction	No, this is a concept application that applies MES, SPC, sensors, and data analytics to continuously monitor and improve product quality.
Smart maintenance management	Predictive/proactive maintenance strategy using IIoT sensors, AI to monitor equipment status	Aligns maintenance with production schedules, reduces downtime, maximizes asset availability by detecting issues before failures occur	No, this is a concept application that uses IIoT, predictive analytics, MES, and historical equipment data to optimize asset reliability and maintenance scheduling.

Digital technology	What it is	Application in (high-tech) manufacturing companies	Core digital manufacturing technologies?
Smart energy management	Digital energy management using smart meters/analytics to monitor and optimize energy consumption	Collects real-time energy usage data, identifies inefficiencies	No, this is a concept application that combines sensors, IIoT, analytics platforms, and control systems to track and optimize energy usage in manufacturing.
Advanced process control	Automated control systems using advanced algorithms/models to optimize complex manufacturing processes	Enhances process stability/quality/efficiency by continuously updating process parameters. Connects with DCS, SCADA and data historians	Yes
Hyper automation	Advanced automation that combines AI, ML, robotic process automation and IIoT	Streamlining by automating quality control, predictive maintenance, procurement, inventory management	No, this is a concept application that merges RPA, AI, PLCs, MES, and workflow automation to streamline complex processes with minimal human intervention.
Integrated supply chain	Digitally connected supply chain, data across procurement/production/logistics/delivery	Leverage integrated supply chain for real-time view on performance metrics	No, an integrated supply chain connects all stages of production and logistics (suppliers, retailers, etc.), so it goes beyond the manufacturing process boundaries.
Digital enterprise	Organization that fully leverages digital across all business functions	Data-driven processes, connected systems and advanced analytics to optimize product lifecycles/enable smart factories	No, a digital enterprise is about an entire digital organization, so it goes beyond the manufacturing process boundaries.
Manufacturing control tower	Centralized platform that provides near-real-time visibility and unified management of manufacturing operations and supply chain activities	Aggregates data from across the enterprise, enables monitoring, performance analysis, informed decisions on manufacturing and logistics	Yes
Connected workforce	Digitally enabled workforce equipped with mobile devices, wearables and collaboration tools for information and communication	Instant updates, instructions and support for productivity and safety	No, this is a concept application that integrates HMI, mobile devices, AR/VR, and IIoT to enhance worker interaction with machines and systems.
Digital performance management	Monitor, measure, improve operational and employee performance in real-time	Digital dashboards and KPIs to track production efficiency, identify bottlenecks	No, this is a concept application that combines MES, SCADA, ERP, and analytics tools to monitor, evaluate, and optimize production performance in real time.
Smart shopfloor management	Application of digital technologies (IIoT, analytics, automation) to manage/optimize shopfloor operations	Enables real-time monitoring of machines/processes, automates task assignments, enhances visibility	No, this is a concept application that builds on MES, SCADA, smart quality, and maintenance systems to enable coordinated, real-time control of shopfloor operations.
Statistical process control	Quality control method that uses statistics to monitor and control manufacturing processes	SPC uses real-time data to detect deviations, reduce variability, ensure consistent product quality	Yes
Augmented reality	Technology that overlays digital information onto the real-world environment via smart glasses, tablets or phones	AR assists workers with step-by-step assembly instructions, maintenance guidance, remote support, training	Yes
Virtual reality	Immersive technology that simulates real/imagined environments for training, design or process visualization	Manufacturers use VR for development and design of new products through simulations.	No, virtual reality is mostly used in product design virtualization and virtual prototyping, which is not part of the manufacturing process, but the design.

D.2.6. How digital manufacturing technologies can support ESRS impacts

Enterprise Resource Planning (ERP)

- **E1-5:** ERP systems provide real-time monitoring and planning of production processes, which improves equipment efficiency and reduces idle time (SAP SE, 2025). For example, ERP-driven schedule optimization aligns machine usage with lower energy-cost periods, helping to cut overall energy consumption (ECI, 2024).
- **E1-6:** According to Tseng et al. (2021), ERP's integrated planning capabilities help minimize overproduction and waste, which directly reduces associated greenhouse gas emissions.
- **E2-5:** ERP systems enhance traceability of raw materials and finished products, enabling companies to closely monitor the use of hazardous substances throughout the production process (Chen et al., 2020). This helps minimize the consumption of hazardous chemicals by ensuring more precise control and efficient usage.
- **E5-5:** ERP systems track materials and production yields across the entire production floor. By identifying inefficiencies, ERP helps minimize scrap and hazardous waste. For instance, centralized records of material usage and batch tracking can identify excessive yield loss, prompting corrective actions to prevent waste (ECI, 2024).

Advanced Planning and Scheduling (APS)

- **E1-5:** APS systems enable production managers to simulate and test various production plans, optimizing both time and energy usage. For example, high-energy tasks can be shifted to off-peak hours or bundled together to reduce machine start-up cycles (Park et al., 2020). Bertolini et al. (2022) shows that APS can significantly lower energy consumption by aligning production schedules with off-peak or renewable energy periods.
- **E1-6:** By reducing energy consumption, especially electricity, APS indirectly lowers Scope 2 emissions (from purchased energy) (Park et al., 2020). In sectors such as the Dutch high-tech industry, this can have a substantial impact as the energy comes primarily from the national grid. Furthermore, APS integrates energy source information, enabling production managers to select production times or machines with lower emissions intensity, especially when grid emissions fluctuate (Steger-Jensen et al., 2019).
- **E5-5:** Advanced scheduling techniques can significantly reduce material and process waste, directly cutting down on hazardous waste volumes (Trebuna et al., 2022). APS systems, particularly with "green scheduling," optimize production runs by reducing line changeovers, lowering the chances of errors and excess off-spec products. This reduces the need for rework and minimizes material waste, both hazardous and non-hazardous.

Manufacturing Execution System (MES)

- **E1-5:** MES enables real-time monitoring and control over shop floor processes, including energy-intensive operations. This allows operators to make adjustments on the fly to improve energy efficiency (Chien et al., 2018). Modern MES platforms can record real-time energy usage for machines and processes. By integrating key energy performance indicators, such as "Energy per unit," MES allows operators to quickly detect energy spikes and take corrective actions.
- **E2-5:** MES improves product traceability and quality control, which helps minimize off-spec production and rework. These are key contributors to hazardous waste. It also ensures that hazardous materials are used efficiently and correctly, reducing the risk of spills or misapplications (Jamwal et al., 2021). MES-driven automation reduces overproduction and scrap, limiting the amount of potentially hazardous material entering the waste stream (Soplop et al., 2009).
- **E5-4:** MES enforces build-to-order precision, which prevents overproduction and supports "just-in-time" manufacturing, reducing raw material overuse. The system's traceability ensures that expensive high-tech materials are used efficiently, while full Bill of Materials (BOM) control prevents the scrapping of critical components (Kromminga, 2024).
- **S1-15:** MES platforms can integrate real-time production data with workforce management systems to track employee hours, task durations, and shift patterns (Interviewee P2). This functionality allows for automatic alerts when employees approach overtime thresholds or regulatory limits, helping to manage work-life balance effectively (Chromjakova, 2018).

- **G1-1:** MES platforms can integrate digital reporting modules that enable workers to directly log safety incidents or near-misses from the shop floor (Interviewee P2). These systems can be set up to ensure anonymity and rapid escalation to management, supporting ethical behavior and transparency (Abdulgalimov et al., 2020).

Supervisory Control and Data Acquisition (SCADA)

- **E1-5:** SCADA systems enable real-time monitoring and fine-grained control over energy use across the manufacturing floor. By providing operators with detailed feedback on energy flows at the machine or process level, SCADA helps detect and correct energy inefficiencies instantly, reducing electricity consumption, particularly in cleanroom and precision equipment operations (Chien et al., 2018; Jasiulewicz-Kaczmarek and Gola, 2019). SCADA aggregates sensor data from across equipment, enabling detailed monitoring of energy use. Operators can identify energy-intensive machines or processes in real-time and remotely adjust setpoints (such as temperature or speed), smoothing peak loads and reducing waste, for example, by shutting off unused lines (Schneider Electric, 2025; Honeywell International Inc., 2024).
- **E1-6:** SCADA systems can optimize processes remotely, such as fine-tuning heating or cooling loops, reducing fuel and gas usage (e.g., combustion in furnaces or boilers), which in turn lowers CO₂ and HFC emissions. This is especially important in energy-intensive operations like chip fabrication (Honeywell International Inc., 2024).

Programmable Logic Controllers (PLC)

- **E1-5:** Upgrading PLC code, such as using variable-frequency drives and adaptive algorithms, is an effective strategy to reduce chiller electricity use in wafer-fab environments. PLC-driven automation optimizes machine cycles, minimizing energy draw (Enyoghasi and Badurdeen, 2021). PLCs precisely control machinery like motors, valves, and heaters. By optimizing machine cycles with smooth ramp-ups and timely shutdowns, PLCs help minimize unnecessary energy use (Mochuan Drives, 2023).
- **E1-6:** Automated control via PLCs helps prevent unnecessary machine idling, which lowers Scope 1 emissions (Enyoghasi and Badurdeen, 2021). Reductions in machine runtime or more efficient control of heating systems via PLCs help decrease fuel or electricity consumption, directly cutting greenhouse gas emissions. For example, PLCs that manage HVAC or tool power have a significant impact on overall plant emissions (Siemens AG, 2025).
- **E5-5:** PLCs automate repetitive tasks with high precision, minimizing human error. This precision reduces scrap by ensuring fewer off-spec parts and helps avoid wastage of hazardous consumables (such as etchants and gases) by preventing mis-dosing (Rockwell Automation, 2025).

Human-Machine Interface (HMI)

- **E1-5:** HMI systems enhance operator-machine interaction, reducing operational mistakes that can lead to wasted energy, such as unnecessary machine idling or inefficient cycles (Ferreira et al., 2023). HMI systems provide operators with real-time energy and process data, helping them make quick adjustments for more efficient operations (Jasiulewicz-Kaczmarek and Gola, 2019).
- **S1-13:** Dashboards in HMI systems offer user-friendly and intuitive interfaces, improving accessibility, comfort, and ease of use (Contini et al., 2025)). Advanced HMI systems improve the quality of work by making interfaces more intuitive, reducing stress and cognitive overload, which in turn boosts worker satisfaction and productivity (Ferreira et al., 2023).
- **S1-15:** HMI systems can monitor workloads and detect signs of cognitive overload through psychophysiological metrics like electrodermal activity (Liu et al., 2024b). This enables real-time feedback to workers on pacing and the need for rest breaks, helping maintain work-life balance (Interviewee P2).
- **G1-1:** HMI systems can be programmed to include safety reporting features, enabling operators to quickly and discreetly report hazards or unsafe conditions directly from their workstation (Interviewee P2, Abdulgalimov et al. (2020)).

Distributed Control Systems (DCS)

- **E1-5:** DCS systems precisely control complex continuous processes, such as chemical baths or coatings, that are energy-intensive. By tightly regulating process parameters, DCS systems reduce energy waste caused by over-processing or unnecessary heating/cooling, supporting the sector's goals to reduce electricity consumption (Jamwal et al., 2021). Modern DCS platforms can also optimize furnace cycles or plasma processes in real-time, enabling incremental energy savings (Emerson Electric Co., 2025b).
- **E2-4:** DCS systems improve process stability, which leads to fewer off-spec runs (e.g., overruns that require venting), resulting in reduced burning of waste fuel or chemicals and lowering associated emissions (Yokogawa Electric Corporation, 2025).

Cloud-based storage

- **E1-5:** Cloud storage centralizes data, reducing the need for energy-intensive local servers and IT infrastructure. This shift helps create a more efficient energy profile in manufacturing by moving data management to optimized, often renewable-powered data centers (Ferreira et al., 2023).
- **S1-13:** Cloud storage enables remote data access and collaboration tools, supporting more flexible, knowledge-based work arrangements (Ferreira et al., 2023). This improves working conditions and enhances opportunities for inclusion across various sites.

Industrial Internet of Things (IIoT)

- **E1-5:** IIoT sensors collect real-time machine data, enabling precise adjustments to reduce unnecessary energy consumption. For example, detecting equipment running at non-optimal conditions in real-time can trigger immediate corrections to improve energy efficiency (Chen et al., 2020).
- **E1-6:** Real-time IIoT data enables tighter process control, reducing wasted fuel runs. Additionally, IIoT can optimize building systems like HVAC and lighting based on occupancy, which helps lower Scope 1 and 2 greenhouse gas emissions (Robustel Technologies, 2023).
- **E2-5/E5-5:** IIoT systems provide real-time condition monitoring, which allows for early detection of potential equipment failures or process deviations. This helps prevent the production of off-spec materials, thereby reducing hazardous waste generation (Chen et al., 2020).

Edge device

- **E1-5:** Edge devices process data close to its source, reducing the need to transmit large volumes of data to centralized servers, which is energy-intensive (Fedosovsky et al., 2022). By filtering and acting on data locally, such as shutting down idle machines, edge computing helps reduce unnecessary energy use on the shop floor (Ferreira et al., 2023). Edge devices reduce the need to send all data to the cloud, lowering communication energy consumption and latency. This allows for faster responses, such as immediate load shedding when power consumption spikes, yielding small energy savings over time (Cisco Systems, Inc., 2018).
- **E1-6:** Edge devices enable faster, localized responses, preventing process deviations that might lead to excess emissions, such as solvent vapors or acid mist. By enabling decision-making at the point of generation, these devices can shut down or correct systems before emissions escalate (Jamwal et al., 2021).
- **E2-5/E5-5:** Edge devices allow for real-time process corrections, reducing the risk of producing off-spec or contaminated batches. This helps minimize the amount of hazardous material that needs to be scrapped or treated (Ferreira et al., 2023).

Data lake/store/base

- **E1-5:** Data lakes enable advanced energy optimization analytics, such as predictive modeling to reduce energy peaks. This helps manufacturing companies lower their overall energy consumption (Ferreira et al., 2023).

Data historian

- **E1-5:** Data historians log time-series data on equipment operations, enabling detailed trend analysis to pinpoint energy inefficiencies, such as motors drawing excess current or equipment remaining idle for extended periods. This allows for corrective actions to reduce energy consumption (Jamwal et al., 2021).
- **E2-5/E5-5:** Data historians identify process drifts early by analyzing historical trends, helping prevent the production of batches that fall outside quality specifications (Ferreira et al., 2023). This reduces the generation of hazardous scrap.

Industrial connectivity (on-prem)

- **E1-5:** Reliable connectivity between machines, sensors, and systems is essential to implement efficiency measures such as MES and IoT. By eliminating communication delays or errors, industrial connectivity ensures timely control actions that help reduce energy consumption (HMS Networks, 2025).

Digital twin

- **E1-5:** Digital twins simulate and test production processes virtually, allowing manufacturers to optimize settings and reduce real-world trial-and-error, which typically consumes energy (Andronie et al., 2021). Digital twins simulate and optimize processes virtually. By testing scenarios like machine schedules and energy load balancing, digital twins help identify energy-saving opportunities before implementing them (Kaplan, 2023). Furthermore, digital twins simulate and optimize real-world energy use, enabling real-time reductions in energy demand across manufacturing systems (Ma et al., 2022).
- **E1-6:** Lower energy use from processes optimized by digital twins directly reduces Scope 2 greenhouse gas emissions. Additionally, digital twins of building systems can cut HVAC fuel usage, further reducing emissions (Scope 1) (Kaplan, 2023).
- **E5-5:** By modeling the impact of changes in processes or materials, digital twins help avoid physical experiments that could generate hazardous scrap. They also enable early detection of conditions likely to result in defective outputs, reducing waste (Contini et al., 2025).
- **S1-15:** Digital twins enable real-time synchronization of physical and virtual environments, allowing operators to make informed decisions remotely based on the digital twin simulations (Rabah et al., 2018). This can support remote maintenance, potentially improving work-life balance by eliminating the need for commuting (Interviewee P1).

Advanced Process Control (APC)

- **E1-5:** APC optimizes process parameters in real time, ensuring equipment operates at optimal conditions and minimizing unnecessary energy use by avoiding over-processing (Jamwal et al., 2021). Next to that, APC uses advanced algorithms, such as multivariable model predictive control, to continuously optimize process variables. For example, it can adjust temperature profiles or chemical feed rates to maximize yield while minimizing excess heating, thereby reducing energy consumption (Görner et al., 2020).
- **E2-4:** By tightly controlling chemical processes, APC prevents incomplete reactions or accidental releases of volatile compounds, directly addressing air emissions and minimizing pollutant release (Chen et al., 2020). APC improves process stability, reducing the occurrence of off-spec batches that waste fuel or release extra pollutants. By running equipment closer to optimal setpoints, APC also minimizes the need for flaring or venting, common in under-controlled processes.
- **E5-5:** APC smooths process dynamics, which reduces scrap by minimizing variability and consequently decreasing the number of rejects. Additionally, higher overall equipment effectiveness leads to fewer runs to achieve the desired output, which reduces raw material waste (Emerson Electric Co., 2025a).

Manufacturing Control Tower (MCT)

- **E1-5:** MCTs use IoT and data analytics to continuously monitor production, helping reduce energy consumption on the shop floor. For example, an IoT-enabled factory monitoring platform (similar to an MCT) tracks and optimizes equipment usage, avoiding wasteful operation and lowering overall energy consumption. This real-time visibility allows MCT platforms to improve energy efficiency by identifying idle machines or suboptimal settings and flagging them for correction (Sharma et al., 2024).
- **E1-6:** MCTs can “reduce carbon emissions” via predictive maintenance and process optimization. In other words, the same real-time visibility that trims energy use also indirectly reduces GHGs by eliminating waste and inefficiency in manufacturing (Sharma et al., 2024)g.
- **E5-4:** MCTs provide an integrated view of production processes, enabling factories to use raw materials and energy more efficiently. For example, MCTs balance workloads across production lines and enable the reuse of outputs, directly contributing to goals of reducing resource intensity (Sharma et al., 2024).
- **S1-14:** According to Leso et al. (2018), the real-time monitoring and predictive maintenance capabilities of MCTs can help reduce workplace accidents and health issues, promoting a safer working environment.
- **G1-1:** The adoption of MCTs can enhance transparency and accountability in manufacturing operations, contributing to an ethical corporate culture. According to (Roy et al., 2024), organizations that implement technologies promoting transparency are more likely to exhibit ethical behavior and decision-making.

Statistical Process Control (SPC)

- **E1-5:** Stable processes tend to run more efficiently, reducing the need for extra runs (Advantive, 2025). However, the direct effect of SPC on energy consumption is relatively small.
- **E2-4:** SPC enables real-time monitoring of process emissions data, helping identify abnormal emissions early and preventing regulatory exceedances (Corbett and Pan, 2002).
- **E2-5:** Smart quality systems using real-time SPC help detect process drift or equipment malfunctions early, reducing the number of off-spec or defective products that would otherwise need to be scrapped as hazardous waste (Chiarini, 2021).
- **E5-5:** SPC improves process stability, reducing off-spec material that might otherwise be classified as hazardous waste (Corbett and Pan, 2002). By using real-time data to maintain process control and detecting drift early, SPC prevents the formation of out-of-spec batches, reducing scrap and rework. This results in lower waste generation (InfinityQS, 2025).
- **S1-14:** SPC can contribute to occupational safety by preventing incidents through proactive monitoring of processes (Interviewee P1). For example, SPC can be implemented to monitor machinery vibrations, enabling early detection of wear and tear that could endanger employees (Madanhire and Mbohwa, 2016).

Augmented Reality (AR)

- **E1-5:** AR can make energy use more visible and optimized on the shop floor. For example, AR overlays can display real-time energy data for machines and help operators assess and understand energy consumption patterns (Agrawal et al., 2024). In practice, AR-based workflows have been reported to cut resource waste and “effectively use energy”. For instance, one AR solution notes it can help firms “reduce unnecessary resource consumption and effectively use energy” (IIoT World, 2022).
- **E5-4:** AR can support the optimal assembly sequence of parts in manufacturing, which helps ensure the right amount of material is used (Interviewee P2), reducing the risk of material overconsumption (Wang et al., 2013).
- **E5-5:** AR work instructions help drastically reduce assembly errors and rework. PTC highlights how AR aids in defect detection during inspection, avoiding unnecessary scrap (Cavanaugh, 2024).
- **S1-9:** AR lenses can assist employees with disabilities in performing tasks they might otherwise be unable to complete, promoting diversity in the workplace (Interviewee P1). AR can provide step-by-step guidance via visual projections, interactive diagrams, and 3D animations, enabling employees with cognitive impairments to perform complex tasks (Simões et al., 2021). AR can

offer audio-guided instructions and high-contrast or tactile feedback overlays for employees with visual impairments (Simões et al., 2021). AR can assist employees with physical disabilities, such as limited dexterity or mobility impairments, through voice commands or gaze tracking (Büttner et al., 2017).

- **S1-13:** AR helps upskill workers quickly, especially with foreign-language support overlays. It enables a diverse workforce to easily follow visual guidance, aiding in inclusion and training (PTC Inc., 2025).
- **S1-14:** AR provides workers with step-by-step guidance, reducing human error and improving safety in complex manufacturing environments. AR offers step-by-step guidance, reducing human error and improving safety (Verma et al., 2023). AR headsets display live equipment data, enhancing safety by helping workers avoid hazardous zones and collisions (Contini et al., 2025). By instrumenting workplaces with wearables and emotion-sensing tools, AR contributes to advancing ESRS social metrics on safe, inclusive work (Vyskočil et al., 2023).
- **S1-15:** AR enables remote maintenance, allowing technicians to perform repairs without needing to enter the factory, thus improving work-life balance by eliminating the commute (Interviewee P1). AR enables real-time remote maintenance by allowing technicians to share their field of view with remote experts using devices like Head Mounted Displays (HMDs) (Mourtzis et al., 2020).

D.2.7. Interviews design cycle 1

To gather early feedback from potential users, interviews were conducted during the design and development phase of the decision-support tool. Participants were selected based on how well they matched the intended user profile. The goal of these interviews was to evaluate the first iteration of the tool, assess whether the design correctly reflected the requirements, and collect expert input on the practical use of digital manufacturing technologies. This also allowed for validation of the findings from literature with insights from practice, particularly on feasibility and relevance that might not be captured in academic or grey literature.

The interviews were scheduled after a minimum viable product had been developed. This included an outline of the decision-support tool and a preliminary list of relevant digital manufacturing technologies linked to the related ESRS impacts. At this stage, the design was still flexible enough to allow for significant changes based on interview outcomes.

Interview method

Format: semi-structured interviews Before the interviews, participants received a preliminary version of the technology–impact overview, similar to the table shown in D.7. Although this earlier version contained fewer identified links, it introduced participants to the topic and gave them time to reflect. Showing only the overview helped ensure that the discussion focused on insights rather than definitions, making efficient use of the limited time available with each expert. The interview guide is provided in Section D.2.7 below.

A semi-structured interview format was used to combine consistency with flexibility. The interview protocol included steps for introducing the research, obtaining informed consent, and managing data collection. While the guide kept interviews aligned with research goals, it also allowed space to explore topics that matched each participant's experience and background.

Each interview started with a general discussion about how the participant typically approaches digital or sustainability strategy. This helped place the tool in context and understand when and how it might be used. The conversation then turned to the tool interface. A first version had been created in Figma, showing the tool's structure, including placeholders for survey questions, an outline of the Twin Transition maturity assessment, and a sketch of the next-steps suggestion feature. The interviewer explained the interface and walked through each part to provide an overview of how the tool would eventually function. This was followed by a deeper discussion of the tool's design and functionality. The goal was to assess whether the functional, structural, and contextual requirements from Section 4.2 were reflected in the current version, or whether changes were needed.

In the final part of the interview, participants were asked to reflect on the links between digital manufacturing technologies and ESRS impacts. This part followed the interface discussion so that participants would understand how these links would appear in the tool and to what level of detail they would be presented. Participants were asked whether they found the identified links realistic and whether

there were any missing connections. The technology–impact overview was shared on screen to support this discussion and to avoid misunderstandings.

Participant selection

To ensure both parts of the interview, the tool interface and the technology-sustainability links, could be discussed in depth, participants were selected carefully. All interviewees matched the intended user profile. They were involved in the practical side of strategy implementation, rather than in client-facing roles. This allowed them to reflect on the tool's requirements and to speak in detail about specific digital technologies and their possible sustainability impacts. A purposive sampling strategy was used, based on the specific expertise needed and the limited time available. Participants were identified through snowball sampling: earlier interviewees from Section 4.2 suggested colleagues who would be suitable for this phase.

In total, two interviews were conducted. Although this is a small number, it was sufficient for this early design cycle. The purpose of this round was to collect targeted feedback on a first prototype, rather than to conduct a broad validation. It should be noted that both interviewees were employed at Accenture. This means they shared a common organizational background, which is a limitation in terms of diversity of perspectives. Their views may reflect shared practices and assumptions shaped by Accenture's methodologies and working culture. As external consultants, they may not fully represent the internal decision-making dynamics of Dutch high-tech manufacturing firms. Although their close collaboration with clients offers useful insights, certain company-specific factors may not have been fully captured.

Interview participant 1 is a manager in strategy consulting at Accenture, working within the Communications, Media, and Technology (CMT) practice, with a specific focus on the high-tech and semiconductor sectors. They have been in this role for just over two years, following five years of experience working inside a semiconductor manufacturing company. The interviewee has a strong understanding of both digital manufacturing and sustainability topics in the semiconductor industry, gained through direct industry experience and consulting projects.

Interview participant 2 is also a strategy manager at Accenture, with a specific focus on the high-tech sector. They have been working in this role for approximately two and a half years and are primarily engaged with clients in the semiconductor industry in the Netherlands. Their work revolves around strategic topics, often linked to supply chain challenges, spare parts management, and sustainability initiatives.

Data collection

The interviews took place on May 8th and May 12th, 2025. Both interviews were conducted one-on-one over Microsoft Teams and were held in English. Each session was recorded and automatically transcribed using Microsoft Teams' built-in transcription feature. These transcripts were then manually reviewed and corrected, especially where technical terms or sector-specific language were involved. Although time-consuming, this step was important to ensure the accuracy of the data and to faithfully capture participants' input. This revision process also marked the beginning of engagement with the data. While it did not involve formal coding yet, it helped the researcher become familiar with the content and start identifying recurring themes or areas of interest for further analysis.

Data processing

The main goals of the interview analysis were to (1) assess whether the functional, structural, and contextual requirements described in Section 4.1 were met in the current design, and (2) verify or expand the links between digital manufacturing technologies and ESRS impacts that had been identified in literature.

The interview data was analyzed using the same thematic analysis and coding approach described in Section 4.2. After completing the analysis, a summary of results was prepared for each interviewee. These summaries were sent to the participants for feedback. This step allowed for clarification of any points and ensured that the researcher's interpretation of the responses was accurate. It also supported transparency and helped protect participants' anonymity. No changes to the summaries had to be made according to the interview participants.

The interview summaries are included in Section X. The findings related to the tool design and requirements are discussed in Section X. The verified and updated connections between digital tech-

nologies and ESRS impacts are presented in Section D.2.6, where they are integrated with the earlier literature findings.

Pre-interview materials

Matching digital manufacturing technologies to sustainability

- **European Sustainability Reporting Standards (ESRS)** are a comprehensive set of mandatory **reporting standards developed by the European Union** to guide companies in disclosing their environmental, social, and governance (**ESG**) impacts and performance. ESRS numbers (E1-5 to G1-1) are selected based on their relevance for the impacts of **high-tech manufacturing operations**.
- **Digital technologies** (ERP to AR) were selected based on digital manufacturing technologies proposed by Accenture (Industry X) **to improve digital manufacturing operations**. They were reviewed based on the opportunity of **contributing positively to the selected sustainability impacts**.

Table D.7: Overview of which of the selected digital manufacturing technologies relevant to the Dutch high-tech manufacturing sector can support sustainability performance across which ESRS impact categories.

Digital manufacturing technology	E1-5 (Energy consumption and mix)	E1-6 (GHG emissions)	E2-4 (Air pollution)	E2-5 (Use of hazardous chemicals)	E5-4 (Resource consumption)	E5-5 (Waste & circularity)	S1-8 (Representation)	S1-9 (Diversity & inclusion)	S1-13 (Training & skills)	S1-14 (Occupation health & safety)	S1-15 (Work-life balance)	G1-1 (Ethical culture and behavior)
ERP	X	X		X		X						
APS	X	X				X						
MES	X	X		X	X							
SCADA	X	X										
PLC	X	X				X						
HMI	X	X							X			
DCS	X	X	X									
Cloud-based storage	X	X							X			
IIoT	X	X		X		X						
Edge device	X	X		X		X						
Data lake/store/base	X	X										
Data historian	X	X		X		X						
Industrial connectivity (on prem)	X	X										
Digital twin	X	X				X						
APC	X	X	X			X						
MCT	X	X			X	X				X		X
SPC	X	X	X	X		X						
AR	X	X				X			X	X		

Interview protocol

Begin with an introduction of myself and the research. Explain that the goal is to get feedback on the first iteration of the design of the decision-support tool for implementing the Twin Transition for Dutch high-tech manufacturing companies. Emphasize that the interviewee's experiences will be valuable. Ask if the interviewee has any questions about the consent form. Repeat the consent elements previously shown to the interviewee during the before provided and signed consent form. Ask for a brief introduction of the interviewee. Verify the name and current role of the interviewee.

1. Starting questions

These questions are aimed at understanding the background and expertise of the interviewee and aligning expectations for the interview.

- *Can you briefly describe your role and experience in/with the Dutch high-tech manufacturing sector?*
- *How would you rate your knowledge of digital manufacturing in the Dutch high-tech manufacturing sector?*
 - *Slightly knowledgeable, moderately knowledgeable, very knowledgeable or extremely knowledgeable?*
- *How would you rate your knowledge of sustainability in the Dutch high-tech manufacturing sector?*
 - *Slightly knowledgeable, moderately knowledgeable, very knowledgeable or extremely knowledgeable?*
- *Can you please describe your current approach to developing digital and sustainability strategies for clients?*
 - *What kind of tools, frameworks or methodologies do you currently use?*

2. Tool design [Figma]

Start with the tool design because then the interviewee has an overview of how the tool will look like and how the tool inputs discussed later in the interview will fit in, so they can tailor their answers in that direction. Let's go through the tool together. I will open the tool and click through it and give some explanation of what is visible on screen.

Overall:

- *What is your first impression of the decision-support tool?*
- *Does it feel like a tool you could use in your work? Why (not)?*

Functionality:

- *From your perspective, what do you see as the main goal of this tool?*
 - *How do you think it can help users in their decision-making process?*
 - *Where do you think the tool provides the most value?*
 - *Where do you think it might fall short?*
- *Which features of the tool seem useful to you?*
 - *Dimension split*
 - *KPIs*
 - *Industry benchmarking*
 - *Next steps*
- *Are there any features or functionalities that you think need to be adjusted or reconsidered?*

Structure/use:

- *Do the three parts in the tool make sense to you (survey, maturity assessment, next steps)?*
 - *Additions?*
 - *Removal?*
 - *Alternatives?*
- *Are the visualizations clear and do they help you make sense of the data and insights presented?*
 - *Do they strike a good balance between high-level overview and detailed information?*
- *If you could change one thing about the tool to improve your experience, what would it be?*

3. Tool inputs [link-table]

Discussion about identified connections between digital manufacturing tools and sustainability impacts. Verification, specification and additions.

Overall:

- *Which connections between digital technologies and sustainability impacts feel intuitive to you?*
- *Were there any links that surprised you or seemed unexpected?*
- *In your experience, which technologies do you see as most impactful for supporting environmental, social, and governance (ESG) sustainability goals?*
 - *Can you rank them or elaborate on why certain technologies stand out to you?*
- *Which technologies do you feel have limited potential for supporting sustainability goals?*
 - *Do you think these technologies could be used in a different way to have a greater impact on*

sustainability?

- *Do you see any links between digital tools and sustainability impacts that are missing from this overview?*

Digital:

- *Do you see any technologies that have limitations in use in the Dutch high-tech manufacturing sector or do not apply?*
 - *E.g. AR HoloLens not ASML because of privacy/security reasons?*
- *Do you miss any technologies that you think should be included in the assessment?*
 - *E.g. are there any emerging technologies that could play a role in sustainable manufacturing?*

Sustainability:

- *Do you see any limitations in using the technologies currently listed in the tool for sustainability goals?*
- *The environmental sustainability dimension seems well-represented, but the social and governance dimensions are less emphasized. How do you see technology playing a role in these areas?*

4. Closing question

- *Is there anything else you would like to share that we have not discussed yet?*

Interview summaries

Interviewee 1 The interviewee finds the decision-support tool generally well-conceived and logically structured. P1 describes it as "well connected" in terms of flow and appreciates that it doesn't stop at maturity assessment but progresses to actionable recommendations: "We don't stop at just saying, yeah, you need to improve here, but how do you improve? So, that's a good connection."

P1 particularly values the tool's capability to support consultants in early stages of client engagement, describing it as "the first part of the pipeline towards building a proposal for a client." P1 emphasizes that such tools help consultants move from identifying needs to proposing concrete initiatives, for example: "If you want to decrease your greenhouse gas emissions by 10% within the next three years, then you need to implement this, which came out of your framework." The participant underscores the potential value the tool could add by enabling consultants to approach clients proactively: "So it's, let's say the first part of the pipeline towards building a proposal for a client."

Structure

The interviewee confirms the general structure makes sense but points out several areas needing refinement:

- P1 points out that while the ESG framework is well-known and relevant, the connection between the assessed dimensions (people, process, policy) and ESG outcomes needs to be explicitly articulated, so users can understand how improvements in these areas translate to specific sustainability gains: "Have you thought of how you're going to do that for people and process dimensions?"
- P1 suggests that the definitions and conceptual underpinnings of the rings (maturity levels) should be more explicit for the user: "Whenever you finalize your tool, it would be good to have, maybe for reference of whomever is utilizing it, what frameworks are being utilized."
- P1 recommends including a reference table or appendix that explains each maturity level and what they imply for different dimensions: "At least make it available for them to see what each of these levels mean."
- P1 stresses the need to highlight the gap between current maturity and strategic ambition directly in the visualization: "Here I have their current status, so then immediately highlight their goal, like this is where your gap is."
- Regarding data inputs, P1 warns that many client ambitions might be qualitative or ambiguous. The tool should accommodate both quantitative and qualitative inputs: "If your tool can handle that and take that as input and then provide something strict, something concrete... then that would... bring it to the next level."
- P1 warns that without a structured hierarchy of KPIs and dimensions, users might feel overwhelmed by data, advocating for a top-down approach where aggregated scores are presented first, with the possibility to drill down into details: "If you hit them immediately with a bunch of data... then you run the risk of losing people."

Links between digital technologies and sustainability

The interviewee confirms many of the links in the provided technology-sustainability impact table make conceptual sense, such as ERP systems contributing to efficiency and thus sustainability: "That does make conceptual sense."

However, P1 offers a critical perspective regarding the practical application of these links in real business settings. P1 cautions that in daily operations, attributing exact sustainability impacts to specific technologies is highly complex and often unrealistic because technologies do not operate in isolation. P1 elaborates: "Making that actual connection on a real-life business setting is a bit complicated because there are a lot of factors at play that might interfere with measuring your decrease in use of hazardous chemicals."

P1 stresses that multiple initiatives, projects, and everyday business activities happen simultaneously across the company, all of which could contribute to or interfere with observed changes in sustainability indicators. Therefore, isolating the impact of a single technology implementation is methodologically challenging, if not impossible, in many cases.

Given these complexities, P1 insists that the tool must always make transparent its assumptions and limitations, and where possible, present ranges rather than fixed estimates of impact. P1 suggests: "Be transparent, provide assumptions, and most likely it's better that you say, based on those assumptions, that you provide a range."

Regarding the use of APS systems to align production schedules with renewable energy availability, P1 acknowledges the conceptual validity but explains that in industries like semiconductors, which operate continuous production processes running 24/7, it's very difficult to adapt schedules without jeopardizing product quality or throughput. While rebalance of production might be possible in theory, P1 views it as highly challenging in practice due to the delicate and inflexible nature of semiconductor manufacturing processes: "It's very continuous... it's complicated because... you need to have all of these processes that are different running, and it's not like you can shut down one of those processes."

Regarding social and governance dimensions, P1 notes they are harder to connect but offers practical insights:

- For social aspects, P1 mentions examples where technologies like augmented reality support disabled workers: "We saw examples of... specific lenses that would help people to perform certain type of work without or people with disabilities perform certain type of work."
- On digital twins combined with AR, P1 suggests they can enable remote maintenance, allowing those who cannot physically enter factories to participate: "Maybe someone... in a wheelchair... can perform maintenance without having to go inside the fab."
- On work-life balance, P1 agrees that remote work facilitated by digital tools can improve it, though P1 stresses this needs clear assumptions: "You would have to explain that very thoroughly and say that is the assumption because there are no studies behind that."
- For health and safety, P1 suggests technologies like statistical process control can contribute indirectly by preventing safety incidents through proactive monitoring: "You can more accurately prevent events from happening, thus keeping, let's say, safety incidents at bay." However, P1 clarifies that many manufacturing plants, especially in semiconductors, already have sophisticated monitoring systems in place for critical variables, and thus the additional contribution of SPC would lie not in basic monitoring itself, but in enabling more advanced statistical analyses that can support preventive safety strategies rather than merely reactive responses.

Regarding governance, P1 admits it is a weak link for digital manufacturing technologies: "It's a tough one." P1 mentions that sourcing rare metals ethically could be the closest link but that it's more about supply chain and not manufacturing directly.

P1 closes by recognizing the complexity and nuances of the semiconductor industry, especially the strict IP controls in fabs, making certain technologies (like AR) difficult to implement externally: "In-fab connectivity is a very, very difficult thing for [an equipment manufacturer] to have within a customer fab."

Interviewee 2

The interviewee appreciated the initial design and overall concept of the decision-support tool, highlighting that the chosen framework of "people, process, policy" is well-recognized and resonates with clients: "I like the people process policy, we're looking at it because indeed it is something that we use a lot, but we also use it a lot because it resonates a lot with our clients."

They emphasized that the tool's main value lies in supporting structured self-reflection for clients as well as consultancy work. The interviewee particularly liked the trade-offs feature in the tool, where it shows both the sustainability gains and losses of implementing a technology. The interviewee saw additional value in the alignment of the tool's technology suggestions with reporting: "Maybe for some [companies], you can say, okay, this could help. This could be some of the gains, right? Like, if you do this, it could lead to easier reporting."

Structure

The interviewee found the general structure logical, with the steps of survey, maturity assessment, and improvement suggestions making sense overall: "So far it makes sense." However, they pointed out areas where the structure could be refined:

- **Role segmentation at the start:** They recommended adding a step at the beginning where users identify their scope of control and knowledge: "Maybe even having the segmentation in the beginning where you ask the person who's filling this in, what can we give you answers on and what is maybe beyond their scope of control?" This should then also translate into the recommendations at the end, as it should be aligned with the survey responder.
- **Scope labels:** The interviewee suggested that adding scope labels (such as Scope 1, Scope 2) might make it easier for organizations to delegate parts of the survey to relevant roles: "At some point you're going to want people to fill in the survey. And I think you might find it that different people within an ESG team are responsible for different parts of the ESG goals."
- **Interlinkages challenge:** They acknowledged the difficulty of strictly separating people, process, and policy, since all dimensions are deeply interlinked: "They're so incredibly interlinked that it's very, very difficult to untangle sometimes."
- **Other metrics than ROI:** They stressed that the presentation of ROI might be too challenging, given the complexity and variability between companies: "The ROI part is probably going to be a bit challenging because it's going to be a bit difficult to prove or measure." Instead, they suggested using more practical and subjective metrics like: (1) Effort to implement: How resource-intensive or difficult it is to implement the measure (rated as low/medium/high). (2) Complexity: How broadly the initiative affects the company, such as whether it requires cross-organizational alignment, touches on customers, suppliers, or even governmental policies. The interviewee underlined that using clear definitions for these metrics would support subjective but structured assessments that remain practical for both internal teams and consultants.
- **Priorities of companies:** The interviewee stressed that the tool should reflect not just the current maturity, but also the company's own ambition level, as goals and priorities differ widely between organizations. They recommended that the tool integrates this by explicitly asking users about their ambitions in the survey phase. The maturity assessment should then present the results in a step-wise manner: (1) Where are you now? (2) What is your ambition (next 5-10 years)? (3) What is the gap with the ideal/most sustainable state? They emphasized that this approach avoids imposing one-size-fits-all recommendations and ensures that the technologies suggested are aligned with the company's own ambitions. Otherwise, there is a risk of proposing overly ambitious technologies that the company has no intention of adopting.
- **Reporting integration visibility:** While the tool is not intended to be a reporting tool per se, the interviewee noted that the way CSRD reporting is integrated into the ESG dimensions should be made more explicit. They appreciated that the KPIs followed the CSRD, but felt this alignment should be made more visible in the interface and explanations, so that users immediately understand that the sustainability dimensions and suggested improvements directly contribute to reporting requirements: "So I noticed that at least a lot of companies are very, very much concerned on reporting itself...I don't know if you're capturing that yet."

Links between digital technologies and sustainability

The interviewee confirmed that most of the proposed links between digital technologies and sustainability make sense, particularly around energy use and efficiency, which are well-covered. However, they noted several gaps and provided practical examples:

- Concrete examples for social and health aspects:
 - Augmented reality (AR): The interviewee cautioned about the use of AR that while it can support disabled employees or enhance training, but facial recognition must be inclusive and reliable: "Primarily they're made to recognize for instance white male faces. So for instance

- facial recognition for Asian, Hispanic, Black employees is definitely not as good."
- Exoskeletons: These were cited as tools to support older employees or reduce repetitive strain injuries.
 - HoloLens and AI for sequence optimization: Used both for training and problem-solving, AI could also optimize manufacturing sequences for efficiency and sustainability.
 - Governance links through digital tools: They gave examples of how digital tools are used for ethical behavior, like QR codes for anonymous reporting of unethical behavior: "There is quite a bit of that as well...they do have QR things in their bathrooms which tie you into, kind of reporting, anonymous reporting, of unethical behavior." This way, digital tools can support ethical work floor behavior by enabling speaking up and reporting unethical behavior.
 - Work-life balance and digital tools: Digital time-tracking tools are used to monitor workloads and ensure work-life balance, offering automatic alerts if employees work excessive hours.
 - Material use and waste interlinkage: They confirmed the close connection between material use and waste. Furthermore, digital tools can enable reuse and remanufacturing by keeping better track of materials (what is available and in what state). But the interviewee stressed that the digital tools need to capture nuances such as differentiating between parts, tools, and consumables in material impacts.

D.3. Maturity model development: level definition

Table D.8: Overview of the selected systematic review papers with title and focus summary.

Authors	Title	Focus
Angreani et al. (2020)	Systematic Literature Review of Industry 4.0 Maturity Model for Manufacturing and Logistics Sector	Reviews 17 digital maturity models to evaluate how they assess readiness for smart manufacturing. Classifies models by purpose (e.g., evaluation, roadmap). Emphasizes the gap between theoretical models and industrial deployment.
Souhail et al. (2023)	Maturity Models as a Support for Industry 4.0 Implementation: Literature Review	Reviews 14 digital maturity models across dimensions like scope, structure, and evaluation methods. Emphasizes importance of multidimensional assessment.
Ünlü et al. (2024)	Readiness and maturity models for Industry 4.0: A systematic literature review	Reviews 22 digital maturity models to determine which are the most applicable for practical use in manufacturing. Classifies models by coverage (readiness vs maturity) and sector specificity.
Vance et al. (2023)	Smart manufacturing maturity models and their applicability: a review	Reviews 24 (19 peer-reviewed, 5 consultancy) digital maturity models with an emphasis on their applicability. Evaluates models on their usability, scope, and validation.

D.4. Maturity model development: populating

D.4.1. Digital manufacturing technologies at each digital maturity level

Table D.9: Overview of digital manufacturing technologies at each of the digital maturity levels, from descriptive to adaptive.

Technology	Descriptive	Diagnostic	Predictive	Prescriptive	Adaptive
ERP	Supply production plans, BOM to shop floor systems	Compare plan vs. actual performance	Simulate demand/design scenarios	Auto-generate optimized plans/design changes	Self-adjust BOMs or schedules in response to factory feedback
ERP	MES/SCADA/IIoT	MES/Data historian/IIoT	APS/Cloud storage/Data lake/IIoT	APS/MES/IIoT	APS/MES/Digital Twin/IIoT

Technology	Descriptive	Diagnostic	Predictive	Prescriptive	Adaptive
APS	Provides basic visibility of production plans	Analyzes delays, bottlenecks	Predicts throughput, shortfalls, delays	Optimizes plans using mathematical models	Autonomous APS dynamically adjusts in real time
APS	ERP/MES/IIoT	MES/SCADA/Data historian/IIoT	IIoT/Data lake/Data historian	Digital Twin/MES/IIoT	Edge IIoT/MES
MES	Track production counts, quality data	Aggregate reports; trace defects	Predict throughput, quality outcomes	Recommend schedule changes/maintenance slots	Dynamic scheduling based on real-time state
MES	SCADA/PLC/IIoT	SPC/Data historian/IIoT	Data lake/IIoT/Digital Twin	APS/SCADA/IIoT	Digital twin/Edge agents/IIoT
SCADA	Display process status, KPIs	Trend visualization, logging	Alerts from trends	Generate control suggestions	Integrate with AI agents for autonomous oversight
SCADA	PLC/DCS/IIoT	Historian/IIoT/SPC	Edge/Data lake/IIoT	PLC/DCS/IIoT	APC/Edge/IIoT
PLC	Control machines, gather sensor data	Analyze control loops for issues	Predict drift/-maintenance	Auto-implement optimized control	Adaptive logic updates parameters via AI
PLC	IIoT	SCADA/Data historian/IIoT	Data historian/Edge device/IIoT	APC/Digital Twin/IIoT	Edge/IIoT
HMI	Display process status, KPIs	Trend visualization for root cause	Alerts from trends	Generate control suggestions	N/A
HMI	SCADA/MES/IIoT	Data historian/IIoT	MES/APS predictions/IIoT	SCADA	
DCS	Control machines, gather sensor data	Analyze control loops for issues	Predict drift/-maintenance	Auto-implement optimized control	Adaptive logic updates via AI
DCS	IIoT	Data historian/IIoT	Edge ML/IIoT/Data historian	APC/Digital Twin/IIoT	APS/IIoT
Cloud-based storage	Stores data, dashboards, mobile access	Historical data retrieval	Storage for predictive models	Prescriptive analytics multi-site	Real-time cloud-edge systems coordinate factory-wide
Cloud-based storage	IIoT	Historian/IIoT	Data lake layer/IIoT	APS/APC/IIoT	Edge IIoT
IIoT	Collect, transmit machine data	Local edge analytics	Predictive models on live streams	Push optimized setpoints to machines	Fully integrated CPS with local AI agents
IIoT	Connectivity			To PLC/DCS	
Edge device	Collect, transmit machine data	Local edge analytics	Predictive models on live streams	Push optimized setpoints to machines	Fully integrated CPS with local AI agents
Edge device	Connectivity				Digital Twin
Data lake/store/base	Log/visualize process data	Query histories, analyze faults	Big datasets for ML	Feed integrated data to optimizers	Stream data for real-time ML/control
Data lake/store/base	MES/SCADA/IIoT	IIoT			
Data historian	Log/visualize process data	Query histories, analyze faults	Big datasets for ML	Feed integrated data to optimizers	Stream data for real-time ML/control
Data historian	SCADA/MES/Cloud				

Technology	Descriptive	Diagnostic	Predictive	Prescriptive	Adaptive
Industrial connectivity (on prem)	Collect/transmit machine data	Local edge analytics	Predictive models on live streams	Push optimized setpoints to machines	Fully integrated CPS with local AI agents
Industrial connectivity (on prem)					
Digital twin	Virtual replica reflects current state	Simulate fault scenarios	Run what-if scenarios	Optimize parameters, push updates	Autonomous twin co-evolves with real process
Digital twin	IIoT/Data historian/MES	Edge/IIoT	IIoT/Data historian	APC/PLC/IIoT	IIoT
APC	N/A	N/A	N/A	Computes optimal moves	Self-learning MPC updates models
APC				To PLC/DCS via IIoT	Edge AI/IIoT
MCT	Monitor KPIs, production, inventory	Identify delays, downtime, quality issues	Forecast demand-supply mismatches	Recommend optimal actions	Autonomous coordination using AI
MCT	ERP/MES/SCADA/IIoT	MES/APS/Data historian/Data lake	Data lake/APS/IIoT/Digital Twin	APS/MES/Digital Twin/AI engine/IIoT	Autonomous APS/MES/Digital Twin/Edge AI/IIoT
SPC	Monitor metrics, dashboards	Drill into causes, control charts	Forecast drift, quality prediction	Suggest adjustments to optimize	Automatic SPC adjusts loops, rejects out-of-spec parts
SPC	MES/SCADA/IIoT	Data historian/IIoT	IIoT	MES/PLC/IIoT	IIoT/Edge agents
AR	Immersive data/training	AR pinpoints faults	Simulate in AR for prediction	Overlay instructions to execute	AR bots adapt environment automatically
AR	IIoT/Data historian	Edge/IIoT	Digital Twin/IIoT	MES/APC/IIoT	IIoT

D.4.2. Digital manufacturing technologies at each digital maturity level for each ESRS impact

Table D.10: Digital maturity levels for digital manufacturing technologies for each ESRS impact.

ESRS	Digital Maturity Level				
	Descriptive	Diagnostic	Predictive	Prescriptive	Adaptive
E1-5	ERP provides real-time monitoring of production processes, helping identify inefficiencies in energy use and equipment performance.	ERP pinpoints areas for improvement, such as idle time or inefficient scheduling, to reduce excess energy consumption.	ERP forecasts future energy consumption and demand, enabling better planning and reducing energy waste by aligning production schedules with energy availability.	ERP generates optimized production schedules to minimize energy costs by using resources during off-peak energy periods, reducing overall consumption and carbon footprint.	ERP dynamically adjusts production processes and schedules based on real-time data to prevent unnecessary energy consumption, improving overall operational efficiency and sustainability.

EDDC	Digital Maturity Level				
	Descriptive	Diagnostic	Predictive	Prescriptive	Adaptive
	APS offers a clear view of production plans and resource usage, helping identify where high-energy tasks are scheduled and allowing for initial insights into potential energy inefficiencies.	APS identifies production inefficiencies, including excessive energy consumption due to poor scheduling or resource allocation, and highlights opportunities for better alignment of tasks with energy use patterns.	APS predicts energy demand based on historical and real-time data, allowing for the alignment of high-energy tasks with off-peak hours or renewable energy availability, thus minimizing overall energy consumption.	APS generates optimized production schedules that reduce energy consumption by shifting high-energy tasks to off-peak hours or bundling tasks to reduce machine start-up cycles, significantly lowering energy use.	APS autonomously adjusts production schedules in real time to minimize energy usage, ensuring that energy-intensive tasks are always aligned with off-peak or renewable energy periods, even in dynamic production environments.
	MES provides basic real-time monitoring of energy consumption, helping operators identify energy spikes and inefficiencies in energy-intensive operations, offering insight into potential improvements in energy usage.	MES helps identify inefficiencies or energy spikes by tracing energy usage back to specific machines or processes, allowing operators to pinpoint areas where corrective actions can be taken to reduce energy consumption.	MES uses predictive analytics to forecast energy consumption based on historical production data, helping operators anticipate energy-intensive operations and adjust processes to minimize unnecessary energy usage.	MES suggests production schedule adjustments or maintenance actions to reduce energy usage, for example, by aligning energy-intensive tasks with off-peak hours or suggesting machine maintenance to prevent energy spikes.	MES dynamically adjusts production schedules in real time to optimize energy usage, automatically shifting tasks to machines or times when energy consumption is lower, helping reduce overall energy use and improve efficiency.
	SCADA provides basic visibility into energy consumption at the machine or process level, allowing operators to detect energy inefficiencies and identify energy-intensive areas, setting the stage for energy reduction actions.	SCADA aggregates sensor data and visualizes trends, helping operators identify the root causes of energy inefficiencies, such as machines running at high speeds or idle times, which can then be addressed to reduce electricity consumption.	SCADA generates alerts when energy usage or process parameters (like temperature) exceed predefined thresholds, allowing operators to address potential inefficiencies or breakdowns before they lead to excessive energy consumption or waste.	SCADA generates recommendations for energy optimization, such as reducing the speed of energy-intensive machines or shutting off unused lines, helping operators fine-tune settings to minimize electricity consumption and improve overall energy efficiency.	SCADA autonomously adjusts process parameters in real time based on AI analysis, optimizing energy usage without operator intervention, such as dynamically managing energy loads and preventing waste by shutting off unused lines or adjusting settings based on real-time data.
	PLCs provide real-time data on machine performance, enabling operators to monitor energy consumption and detect inefficiencies in equipment such as motors and heaters, providing a foundation for energy-saving actions.	PLCs analyze data from control loops to diagnose issues such as instability in machine operation, which may cause inefficient energy consumption, helping operators address problems that contribute to higher energy use.	PLCs use predictive capabilities to identify drift or anomalies in machine control loops, triggering alerts for preventive maintenance to avoid energy waste due to malfunctioning equipment or suboptimal settings.	PLCs implement optimized control strategies (e.g., model predictive control) to automatically adjust machine cycles, reducing unnecessary energy consumption by ensuring machines operate at optimal efficiency.	PLCs autonomously optimize machine operations by using AI models to adjust parameters, ensuring energy-efficient performance over time, such as reducing unnecessary energy draw by optimizing ramp-ups and shutdowns.

EDDC	Digital Maturity Level				
	Descriptive	Diagnostic	Predictive	Prescriptive	Adaptive
	HMI systems provide operators with real-time visibility into machine status and energy consumption, enabling them to identify potential inefficiencies, such as idle machines, that lead to wasted energy and increased emissions.	HMI systems allow operators to analyze trends and root causes of inefficiencies, such as energy waste from excessive machine idling or prolonged cycles, enabling corrective actions that reduce energy consumption.	HMI systems use predictive capabilities to generate alerts when trends indicate potential inefficiencies, such as rising temperatures or abnormal energy usage, allowing operators to take action before energy waste occurs.	HMI systems provide actionable recommendations to operators, such as adjusting cycle times or stopping idle machines, to optimize energy use and prevent unnecessary consumption, directly contributing to energy savings.	N/A
	DCS systems provide real-time monitoring and control of energy-intensive processes, offering visibility into energy usage and identifying potential inefficiencies such as over-processing or excessive heating/cooling, laying the foundation for energy reductions.	DCS systems help analyze data from control loops, diagnosing issues like energy overuse caused by unstable or inefficient process control, allowing operators to pinpoint inefficiencies and reduce energy consumption.	DCS systems use predictive capabilities to detect early signs of inefficiencies or drift in control loops, forecasting potential energy waste before it occurs, allowing operators to take corrective action and reduce unnecessary energy consumption.	DCS systems implement model predictive control (MPC) to automatically adjust process parameters, optimizing furnace cycles or plasma processes in real-time, significantly reducing energy consumption by minimizing over-processing and unnecessary heating or cooling.	DCS systems autonomously adjust process parameters in real-time using AI models, optimizing energy usage by continuously adapting to changing conditions and preventing energy waste, further driving down electricity consumption.
	By centralizing data storage, cloud-based systems reduce the need for energy-intensive local servers, leading to a reduction in on-site energy consumption and a more efficient energy profile for manufacturing. Data management is moved to optimized, often renewable-powered data centers, improving sustainability.	Cloud storage enables easier diagnostics across multiple systems and production lines, allowing manufacturers to identify inefficiencies. By pinpointing energy-intensive operations, cloud-based systems help reduce energy consumption and minimize waste, directly contributing to lower emissions.	Scalable cloud storage allows the aggregation of data from multiple sites, enabling predictive modeling that identifies future energy inefficiencies. This supports energy optimization strategies by forecasting potential inefficiencies, helping companies take proactive measures to reduce energy use and emissions.	By integrating cloud storage with optimization engines, it allows for real-time energy load balancing across multiple sites, ensuring energy is used more efficiently. This reduces overuse and waste, lowering Scope 2 emissions through better energy distribution across sites.	Cloud-edge systems enable real-time coordination across distributed sites, using adaptive algorithms to optimize operations and energy use. This continuous adjustment helps to dynamically reduce energy consumption, avoid waste, and improve energy efficiency factory-wide, driving significant reductions in Scope 2 emissions.

ECDC	Digital Maturity Level				
	Descriptive	Diagnostic	Predictive	Prescriptive	Adaptive
	IIoT systems provide real-time data on machine performance, allowing operators to detect inefficiencies, such as machines running at non-optimal conditions. This visibility helps identify energy waste and provides the basis for corrective actions that reduce unnecessary energy consumption.	IIoT systems analyze real-time sensor data locally to detect operational anomalies or inefficiencies. By identifying equipment running at non-optimal conditions (e.g., idle time or overworking), they enable timely corrective actions to reduce energy waste and improve overall energy efficiency.	IIoT systems run predictive models on sensor data to forecast potential inefficiencies, such as machinery requiring maintenance or running at sub-optimal efficiency. This proactive approach allows adjustments before inefficiencies impact energy consumption, preventing waste and contributing to energy savings.	IIoT systems automatically adjust machine settings in real-time by pushing optimized setpoints, such as reducing speed or adjusting temperature, to improve energy efficiency. These real-time adjustments minimize energy consumption and enhance sustainability by ensuring that machines are always operating at their most efficient levels.	Fully integrated IIoT systems with local AI agents autonomously optimize machine operations based on real-time data, continuously adjusting settings to ensure energy efficiency. This autonomous coordination reduces unnecessary energy consumption, enhances efficiency across operations, and significantly lowers emissions by adapting operations to real-time needs.
	By collecting and transmitting real-time data on energy consumption and machine performance, edge devices enable operators to monitor and identify areas of inefficiency. This helps reduce unnecessary energy consumption by improving visibility into energy use, optimizing machine efficiency, and reducing waste.	Edge devices locally analyze real-time data to detect inefficiencies, such as machines running at suboptimal energy levels. By identifying these anomalies, immediate corrective actions can be taken to prevent excessive energy consumption and optimize machine performance, improving overall energy efficiency.	Edge devices use predictive models to forecast when energy consumption will peak or when a machine will operate inefficiently. This foresight enables proactive adjustments, such as reducing power consumption during peak demand periods or scheduling maintenance before energy use spikes, leading to better energy efficiency and reduced consumption.	Edge devices send real-time optimized instructions to machines, adjusting parameters such as speed, temperature, or load to ensure machines operate at their most energy-efficient settings. These adjustments prevent energy waste, improve process efficiency, and reduce energy consumption over time.	Fully integrated edge devices with adaptive capabilities autonomously optimize machine operations in real time, adjusting energy usage based on real-time data inputs. This continuous, dynamic adjustment ensures that energy is used efficiently, reducing waste and maintaining optimal energy consumption without manual intervention.
	Data lakes centralize energy consumption data, enabling manufacturers to identify historical peaks and inefficiencies. This foundational visibility allows for targeted actions to reduce energy consumption and avoid excessive energy use in the future.	By enabling deeper analysis of past energy usage and identifying inefficiencies, data lakes help diagnose areas of high energy consumption, such as production faults or equipment inefficiencies, reducing energy waste and improving efficiency.	With predictive capabilities, data lakes enable the development of ML models that forecast future energy consumption patterns and potential peaks. By predicting these events, manufacturers can implement strategies to prevent excess energy use, leading to lower overall energy consumption.	By feeding data to optimization engines, data lakes allow manufacturers to implement prescriptive solutions that optimize energy usage. These solutions can balance energy loads, reduce peak consumption times, and adjust processes in real time, leading to significant energy savings and reduced emissions.	In fully integrated systems, data lakes stream real-time data for ML algorithms that autonomously adjust operations based on real-time conditions. These adaptive systems continuously optimize energy use, ensuring that energy is consumed efficiently and reducing unnecessary energy waste, further decreasing emissions.

EDDC	Digital Maturity Level				
	Descriptive	Diagnostic	Predictive	Prescriptive	Adaptive
	Data historians collect detailed historical data, allowing operators to visualize and identify inefficiencies such as motors drawing excess current or equipment remaining idle for extended periods. This insight forms the foundation for reducing energy consumption by highlighting areas for corrective actions.	Data historians enable in-depth analysis of historical data, allowing for the identification of inefficiencies like energy spikes or prolonged idle times. These diagnostics enable manufacturers to pinpoint the root causes of energy waste, leading to targeted actions to reduce energy consumption.	Data historians store large volumes of data that can be used to train predictive models, helping forecast energy inefficiencies and potential peaks. This predictive capability allows for proactive adjustments to minimize future energy waste, leading to more efficient energy use.	By providing integrated data to optimization engines, data historians support real-time decision-making that helps optimize energy consumption. These recommendations include load balancing, operational scheduling, or adjustments to equipment settings, reducing excess energy usage and lowering overall consumption.	Fully integrated data historians support real-time machine learning applications, enabling autonomous adjustments to processes that optimize energy usage. These adaptive systems continuously analyze energy consumption data and adjust operations in real-time, ensuring continuous improvement in energy efficiency without human intervention.
	Reliable connectivity ensures that data from machines and sensors is transmitted to SCADA/MES systems without delays. This visibility helps operators monitor energy consumption in real-time, enabling quicker identification of inefficiencies and promoting actions to reduce energy consumption.	By enabling local edge analytics, industrial connectivity helps detect inefficiencies or deviations in real-time, such as machines running at high energy consumption levels. Early detection leads to corrective actions that reduce energy waste and improve overall efficiency.	Industrial connectivity allows edge devices to run predictive models on live sensor data, forecasting when machines are likely to consume excessive energy or fail. By anticipating inefficiencies, proactive measures can be taken to reduce energy consumption before problems arise.	By feeding optimized setpoints to machines in real-time, industrial connectivity helps adjust operational parameters to optimal energy-efficient settings. This reduces unnecessary energy consumption and ensures machines operate at peak efficiency, leading to energy savings across processes.	In fully integrated CPS, industrial connectivity enables autonomous coordination of devices through local AI agents. This ensures continuous, real-time optimization of energy consumption, making adjustments on the fly to minimize waste and improve energy efficiency across operations.
	By creating a virtual representation of real-world systems, digital twins provide manufacturers with insights into current energy consumption and process states. This allows for the identification of inefficiencies, which can be addressed to reduce energy usage and improve efficiency.	Digital twins simulate potential faults and inefficiencies in production processes, helping to identify situations that could lead to energy waste, such as machine malfunctions or inefficient operational conditions. By diagnosing these issues virtually, manufacturers can avoid energy waste before it occurs in the real system.	By running predictive “what-if” scenarios, digital twins allow manufacturers to anticipate energy consumption outcomes under various operational settings. This helps optimize energy usage before making physical changes, reducing trial-and-error and minimizing energy waste in the actual production environment.	Digital twins allow manufacturers to optimize process parameters in the virtual model and then implement these updates in the real world. This helps achieve optimal energy consumption, ensuring that machines operate at peak efficiency and reducing unnecessary energy use across the manufacturing process.	In a fully integrated system, digital twins enable real-time optimization of energy consumption through a closed-loop control system. The virtual and real machines co-evolve, dynamically adjusting operations to minimize energy waste and maximize energy efficiency across the production process.

ECDC	Digital Maturity Level				
	Descriptive	Diagnostic	Predictive	Prescriptive	Adaptive
	N/A	N/A	N/A	By computing optimal moves based on real-time data, APC ensures that processes are operating at the most energy-efficient levels. This helps prevent over-processing and reduces unnecessary energy consumption, leading to lower overall energy usage.	Self-learning MPC optimizes process variables continuously and adapts in real time, ensuring processes are always operating at peak efficiency. This minimizes energy waste by adjusting variables such as temperature profiles and chemical feed rates, resulting in significant reductions in energy consumption over time.
	MCTs track key performance indicators (KPIs) across the plant, giving operators visibility into energy consumption patterns. This allows for the identification of inefficiencies, such as idle machines or suboptimal settings, which helps reduce unnecessary energy consumption and improve overall energy efficiency.	By identifying the root causes of production delays or inefficiencies through integrated data views, MCTs can help detect when energy is being wasted (e.g., during idle periods or machine downtime). This enables corrective actions to improve energy efficiency and reduce unnecessary energy consumption.	MCTs forecast potential production issues, including demand-supply mismatches or machine failures. By predicting these issues, MCTs enable proactive adjustments that minimize energy waste, such as adjusting production schedules or machine usage to avoid peak energy consumption periods.	By recommending actions like rescheduling production or rerouting operations, MCTs optimize the use of energy across the entire production floor. These adjustments reduce energy consumption by minimizing inefficiencies such as overproduction or unnecessary machine operation, leading to better overall energy efficiency.	Fully integrated MCTs use real-time AI-driven decisions to autonomously optimize production processes, including energy use. By adjusting operations on the fly, these systems reduce unnecessary energy consumption by ensuring machines and processes always run at optimal efficiency, minimizing waste and improving energy efficiency.
	By monitoring OEE and defect rates, SPC provides insights into process performance. While the direct impact on energy consumption may be small, SPC helps identify inefficiencies that can lead to excess energy use. This visibility contributes to better management of resources, improving overall efficiency.	By diagnosing the root causes of variability, SPC allows manufacturers to address issues that might lead to inefficiencies, such as inconsistent equipment operation. Reducing variability can lead to fewer energy-intensive adjustments, contributing to overall energy savings and process optimization.	Predictive capabilities in SPC help forecast potential process issues before they result in wasteful energy consumption. By anticipating drift and adjusting operations proactively, SPC reduces the need for excessive energy use and ensures more efficient energy consumption over time.	SPC provides real-time recommendations to optimize process parameters, reducing defects and the need for rework. These optimizations prevent overproduction and inefficiencies, which helps lower energy consumption and improves resource efficiency.	Fully automated SPC systems continuously monitor and adjust processes in real time, reducing the occurrence of out-of-spec parts and unnecessary process runs. This not only improves process stability but also minimizes the need for additional energy consumption, contributing to overall energy efficiency.

EDC	Digital Maturity Level				
	Descriptive	Diagnostic	Predictive	Prescriptive	Adaptive
	AR provides a visual representation of energy consumption data on the shop floor, helping operators easily view and assess how much energy machines are using. This visibility allows for better decision-making regarding energy management, contributing to more efficient energy usage.	AR overlays allow operators to quickly identify areas of inefficiency, such as machines running at higher energy levels than necessary. By diagnosing these inefficiencies, operators can take corrective actions to reduce energy consumption, leading to energy savings and reduced waste.	AR can simulate production processes and predict areas where energy consumption might increase or become inefficient. This predictive capability allows operators to anticipate problems before they occur and adjust processes proactively to reduce energy waste, improving energy efficiency on the shop floor.	AR provides real-time guidance on how to perform tasks with energy efficiency in mind, suggesting optimized procedures to minimize energy consumption. By overlaying instructions that promote energy-saving practices, AR directly helps reduce unnecessary resource consumption and improve energy use.	Fully integrated AR systems use real-time data to automatically adjust the virtual environment, optimizing processes to reduce energy consumption. By continuously adapting and updating workflows to reflect the most energy-efficient methods, AR helps minimize resource waste and ensures that energy is used efficiently throughout the production process.
E1-6	ERP provides real-time data on production quantities and waste, helping to identify overproduction and areas where waste can be reduced, minimizing associated greenhouse gas emissions.	ERP analyzes production data to diagnose reasons for overproduction, such as poor demand forecasting, allowing for targeted interventions to reduce waste and emissions.	ERP uses predictive analytics to forecast future production scenarios, identifying potential overproduction or waste, allowing businesses to adjust operations before waste occurs, thereby reducing emissions.	ERP suggests production plans designed to optimize resource use, reduce waste, and prevent overproduction, contributing to a reduction in greenhouse gas emissions associated with excess manufacturing.	ERP dynamically adjusts production schedules based on real-time demand, minimizing waste and overproduction by preventing excess production and reducing emissions in real time.
	APS offers visibility into energy consumption patterns, including electricity usage, helping managers identify areas where energy consumption can be reduced, particularly during high-intensity grid periods.	APS identifies patterns of energy consumption that contribute to Scope 2 emissions, helping pinpoint when and where electricity consumption can be optimized to reduce overall emissions.	APS predicts energy consumption and integrates emissions intensity data to forecast when energy-intensive tasks can be shifted to periods with lower emissions or renewable energy availability, reducing Scope 2 emissions.	APS generates optimized production schedules that reduce energy consumption during high-emission periods by aligning production with times when the grid's emissions intensity is lower, directly reducing Scope 2 emissions.	APS autonomously adjusts production schedules in real time, ensuring energy-intensive tasks are automatically shifted to times with lower emissions intensity, reducing Scope 2 emissions by aligning production with cleaner energy periods.
	MES provides visibility into real-time energy consumption, enabling operators to detect inefficiencies and excessive energy use, which directly impacts Scope 2 emissions by helping reduce energy consumption.	MES identifies patterns of energy use and inefficiencies, allowing operators to pinpoint the root causes of excessive energy consumption, thus enabling targeted actions that help lower Scope 2 emissions.	MES predicts energy consumption and anticipates high-demand periods based on historical data, helping operators optimize energy usage and shift production to times of lower energy intensity, contributing to Scope 2 emissions reduction.	MES generates optimized production schedules or recommends maintenance actions that minimize energy consumption, helping align energy-intensive processes with off-peak times or low-emission periods to reduce Scope 2 emissions.	MES automatically adjusts production schedules in real time to reduce energy consumption, ensuring that energy-intensive tasks are shifted to periods of low energy demand, directly decreasing Scope 2 emissions.

CCDC	Digital Maturity Level				
	Descriptive	Diagnostic	Predictive	Prescriptive	Adaptive
	SCADA provides visibility into fuel and gas usage in real-time, helping operators identify areas where energy consumption could be optimized, offering a foundation for improving process efficiency and reducing CO ₂ and HFC emissions.	SCADA tracks energy consumption patterns and helps diagnose inefficiencies in heating or cooling loops, such as overuse of fuel or gas, pinpointing areas for improvement to reduce emissions like CO ₂ and HFCs.	SCADA uses predictive analytics to forecast future inefficiencies, such as increased fuel or gas usage in heating or cooling systems, enabling operators to take preventive actions before emissions increase, thus lowering CO ₂ and HFC emissions.	SCADA generates recommendations to fine-tune heating or cooling systems, such as adjusting temperatures or controlling combustion in furnaces or boilers to minimize fuel use, directly reducing CO ₂ and HFC emissions.	SCADA autonomously adjusts process conditions (such as heating or cooling loop settings) based on real-time data, optimizing fuel and gas consumption to lower CO ₂ and HFC emissions without operator intervention.
	PLCs provide visibility into machine usage and energy consumption in real-time, helping operators identify where unnecessary idling or inefficient operations occur, offering a foundation for reducing Scope 1 emissions through optimized control.	PLCs analyze operational data to detect inefficiencies like machine idling or excessive heating, helping diagnose and address areas where fuel or electricity consumption can be reduced, thereby lowering Scope 1 emissions.	PLCs predict equipment failures or inefficiencies, like malfunctioning HVAC or tool power systems, which may lead to unnecessary fuel or electricity consumption, enabling preventive actions that reduce CO ₂ emissions by minimizing energy waste.	PLCs automatically adjust machine settings or HVAC system parameters to minimize energy consumption, such as by preventing unnecessary machine idling or optimizing heating systems, directly reducing Scope 1 emissions.	PLCs use adaptive logic to autonomously adjust machine or HVAC control systems in real-time, optimizing energy use and minimizing CO ₂ emissions by dynamically managing tool power and heating/cooling cycles without operator intervention.
	HMI systems provide visibility into real-time energy consumption and process status, enabling operators to identify areas where energy use is high and take action to reduce Scope 2 emissions by minimizing unnecessary energy usage.	HMI systems aggregate and analyze energy consumption data, helping identify inefficiencies like idle machines or energy use during non-optimal times, providing insights that help reduce energy consumption and Scope 2 emissions.	HMI systems predict potential inefficiencies by analyzing trends and forecasting energy usage spikes, allowing operators to adjust processes proactively, preventing energy waste, and reducing Scope 2 emissions.	HMI systems suggest process adjustments to optimize energy consumption, such as stopping idle machines or adjusting operational parameters, directly contributing to Scope 2 emission reductions by reducing energy waste.	N/A
	DCS systems provide real-time energy monitoring, helping identify inefficiencies in energy-intensive processes, such as over-processing or excessive heating/cooling, providing a foundation for reducing energy use and Scope 2 emissions.	DCS systems diagnose operational inefficiencies that lead to increased energy consumption, such as overuse of energy during heating/cooling cycles or unstable control, enabling targeted corrective actions to lower energy usage and Scope 2 emissions.	DCS systems predict when energy inefficiencies might arise due to drift in control loops or other operational issues, allowing operators to proactively adjust processes before energy waste occurs, resulting in lower Scope 2 emissions.	DCS systems reduce energy consumption by automatically implementing optimized control strategies like MPC, which fine-tune processes such as furnace cycles or plasma operations in real-time, minimizing energy use and Scope 2 emissions.	DCS systems autonomously adjust energy usage by continuously optimizing process parameters with AI models, ensuring the system operates at peak energy efficiency without human intervention, resulting in continuous Scope 2 emission reductions.

EDC	Digital Maturity Level				
	Descriptive	Diagnostic	Predictive	Prescriptive	Adaptive
	Centralizing data storage in the cloud reduces the need for energy-intensive local servers and IT infrastructure, shifting data management to optimized, often renewable-powered data centers, contributing to a more efficient energy profile and reducing Scope 2 emissions.	By analyzing historical and real-time data across systems and production lines, cloud-based storage helps identify energy inefficiencies and underutilized processes, allowing manufacturers to make adjustments that reduce unnecessary energy consumption and Scope 2 emissions.	Cloud-based storage enables the aggregation of data across multiple sites, which facilitates the development of predictive models for energy optimization. This forecasting helps identify and mitigate inefficiencies before they arise, ultimately reducing energy consumption and Scope 2 emissions.	By integrating cloud storage with optimization engines, manufacturers can implement multi-site prescriptive analytics, ensuring energy loads are balanced across locations, which improves energy efficiency and reduces Scope 2 emissions by preventing overuse and waste.	Cloud-edge systems enable real-time, adaptive optimization of energy consumption across multiple sites. These systems autonomously adjust operations in real time, reducing unnecessary energy consumption and improving energy efficiency across sites, leading to continuous reductions in Scope 2 emissions.
	IIoT systems provide foundational real-time data on machine operations and building systems like HVAC and lighting. This data enables operators to monitor energy consumption, detect inefficiencies, and make adjustments that reduce wasted fuel use and lower Scope 1 and 2 CO ₂ emissions.	IIoT systems analyze data locally to detect issues like HVAC running inefficiently or lighting being left on in unoccupied areas. By diagnosing these inefficiencies, IIoT systems help prevent wasted energy use, reducing Scope 1 and 2 CO ₂ emissions by ensuring energy is only used when necessary.	IIoT systems use predictive analytics to forecast when inefficiencies in systems like HVAC or lighting will occur. By anticipating these inefficiencies, operators can take proactive measures to adjust systems before excessive energy consumption happens, helping reduce Scope 1 and 2 CO ₂ emissions.	IIoT systems automatically adjust machines and building systems, such as HVAC and lighting, in real-time based on occupancy or process needs. These adjustments minimize energy waste, directly reducing fuel consumption and Scope 1 emissions from heating or cooling and lowering Scope 2 CO ₂ emissions from electricity use.	IIoT systems autonomously adjust HVAC, lighting, and machine settings in real-time based on data inputs, optimizing energy consumption across the factory or building. This continuous optimization reduces wasted energy and CO ₂ emissions, making operations more energy-efficient and lowering Scope 1 and 2 emissions.
	Edge devices provide real-time monitoring of process conditions, enabling early detection of deviations that could lead to excess emissions (e.g., solvent vapors or acid mist). This visibility allows operators to take quick actions before emissions escalate.	By analyzing local data, edge devices can detect process anomalies, such as temperature or pressure deviations, which are indicative of conditions that could lead to emissions. This localized diagnosis allows for immediate corrections, preventing excess emissions from occurring.	Predictive models run on edge devices forecast potential deviations that could result in excess emissions, such as solvent vapors or acid mist. These forecasts enable proactive actions to prevent the escalation of emissions before they happen, improving environmental sustainability.	Edge devices provide real-time recommendations, pushing optimized setpoints to machines to maintain operational stability. This prevents conditions that could lead to excess emissions, ensuring processes stay within safe, sustainable parameters and reducing the risk of waste or hazardous releases.	With fully integrated systems and local AI agents, edge devices autonomously adjust machine operations in real time. This continuous optimization ensures that emissions such as solvent vapors or acid mist are minimized by responding to changes as they occur, without requiring manual intervention, thus reducing environmental impact and improving sustainability.

EDDC	Digital Maturity Level				
	Descriptive	Diagnostic	Predictive	Prescriptive	Adaptive
	Data lakes centralize energy consumption data and provide visibility into past energy usage patterns. This insight helps manufacturers understand where energy is being consumed inefficiently, forming a basis for targeted actions to reduce Scope 2 emissions by addressing energy inefficiencies.	By enabling the analysis of historical energy usage and operational data, data lakes help diagnose inefficiencies and areas where energy consumption can be reduced. This reduces Scope 2 emissions by improving energy efficiency through targeted corrective actions based on past performance trends.	With predictive analytics, data lakes help anticipate energy consumption peaks and inefficiencies before they occur. This foresight enables proactive adjustments to operations, reducing unnecessary energy usage and Scope 2 emissions by ensuring energy is used more efficiently during high-demand periods.	Data lakes integrate with optimization engines to provide real-time data-driven recommendations for energy efficiency. By optimizing energy usage and balancing loads, these recommendations help reduce Scope 2 emissions by preventing energy waste and ensuring energy is used in the most efficient manner across the production process.	Fully integrated data lakes support real-time machine learning applications, enabling autonomous adjustments to processes that optimize energy consumption. By continuously adjusting operations based on real-time data, these adaptive systems reduce energy waste and Scope 2 emissions, ensuring energy efficiency throughout the operation.
	Data historians collect and store historical energy usage data, offering insights into inefficiencies like idle equipment or excessive energy consumption. By identifying these inefficiencies, manufacturers can take action to reduce energy consumption, which leads to a reduction in Scope 2 emissions associated with energy use.	By enabling diagnostic queries of past energy usage and operational trends, data historians help identify areas where energy consumption is higher than necessary. This allows manufacturers to implement targeted improvements, reduce energy waste, and lower Scope 2 emissions by optimizing energy use.	Data historians store large datasets, which can be used to develop predictive models that forecast energy consumption peaks and inefficiencies. By anticipating energy demand and inefficiencies in advance, manufacturers can take proactive measures to optimize energy use, reducing Scope 2 emissions.	Data historians support optimization engines that recommend real-time actions, such as load balancing or adjusting schedules, to minimize energy consumption. By optimizing energy usage across operations, these recommendations help reduce Scope 2 emissions associated with electricity consumption.	With real-time data streaming and machine learning, data historians enable autonomous systems to continuously adjust operations for maximum energy efficiency. These adaptive systems reduce energy consumption by responding in real-time to changes in operational conditions, helping minimize Scope 2 emissions through better energy management.
	Reliable industrial connectivity ensures the transmission of real-time data, enabling operators to identify areas of high energy consumption. This visibility helps reduce energy waste by allowing for immediate corrective actions, contributing to a reduction in Scope 2 emissions by optimizing energy use.	By enabling local edge analytics, industrial connectivity helps detect inefficiencies like energy spikes or equipment running idle. Early diagnosis of these inefficiencies enables corrective actions that prevent excessive energy consumption, helping to lower Scope 2 emissions by improving energy efficiency.	Industrial connectivity allows predictive models to forecast energy consumption peaks and inefficiencies. By anticipating these events, operators can take proactive actions to reduce energy use during high-demand periods, contributing to a decrease in Scope 2 emissions.	By transmitting real-time optimized setpoints, industrial connectivity helps adjust processes to more efficient energy consumption levels. These adjustments prevent unnecessary energy waste and ensure machines operate at peak efficiency, resulting in lower Scope 2 emissions associated with electricity use.	In fully integrated CPS, industrial connectivity enables autonomous systems to continuously optimize energy usage in real-time. This dynamic adjustment of processes reduces energy waste, leading to ongoing energy savings and a significant reduction in Scope 2 emissions by ensuring energy consumption is minimized without human intervention.

CCDC	Digital Maturity Level				
	Descriptive	Diagnostic	Predictive	Prescriptive	Adaptive
	Digital twins help reduce Scope 2 emissions by offering visibility into energy consumption patterns. By identifying energy inefficiencies, such as excess energy use during idle times, manufacturers can address these issues, resulting in reduced energy consumption and lower Scope 2 CO ₂ emissions. Additionally, digital twins of building systems (like HVAC) help optimize energy use, contributing to lower Scope 1 emissions.	By diagnosing potential inefficiencies before they manifest in real processes, digital twins help manufacturers correct issues early, minimizing excess energy consumption and Scope 2 CO ₂ emissions. In building systems, such diagnostics prevent HVAC-related faults that could lead to increased fuel consumption, lowering Scope 1 emissions as well.	Predictive simulations using digital twins allow manufacturers to test energy consumption under different operational scenarios. By predicting energy peaks and inefficiencies, manufacturers can make adjustments in advance to prevent excessive energy use, reducing Scope 2 CO ₂ emissions. Digital twins of HVAC systems help predict fuel use, enabling energy-saving adjustments that further reduce Scope 1 emissions.	By optimizing operational parameters virtually and pushing updates to real-world systems, digital twins ensure machines and building systems, such as HVAC, operate at peak efficiency. This leads to direct reductions in energy consumption, lowering Scope 2 CO ₂ emissions. In HVAC systems, these optimizations cut fuel use, reducing Scope 1 emissions from heating and cooling processes.	Fully integrated digital twins autonomously adjust machines and building systems (e.g., HVAC) in real-time to maintain optimal energy efficiency. These dynamic, adaptive adjustments ensure that energy consumption is minimized continuously, leading to reduced Scope 2 CO ₂ emissions. In the case of HVAC, these adjustments also reduce Scope 1 emissions by cutting unnecessary fuel usage.
	N/A	N/A	N/A	By computing optimal adjustments in real-time, APC ensures that energy is consumed efficiently, preventing over-processing and unnecessary energy use. This real-time optimization helps reduce Scope 2 emissions by lowering the energy consumption associated with inefficient operations.	Self-learning MPC allows APC to adapt in real-time, ensuring that processes continuously operate at their most energy-efficient levels. By dynamically adjusting variables like temperature and chemical feed rates, APC helps to minimize energy waste, resulting in reduced Scope 2 emissions over time.
	By providing real-time visibility into operations, MCTs help identify energy inefficiencies (e.g., idle machines, sub-optimal settings). This reduces energy waste, indirectly leading to lower Scope 2 emissions as energy consumption is optimized, and reduces GHG emissions by improving overall manufacturing efficiency.	MCTs help diagnose operational issues, such as machine inefficiencies or downtime, that lead to wasted energy and emissions. By addressing these inefficiencies and reducing downtime, MCTs not only cut energy use but also reduce associated GHG emissions by preventing excess power consumption.	MCTs use predictive capabilities to forecast potential production disruptions or equipment failures. By anticipating these issues, operators can take proactive steps to reduce energy-intensive problems and avoid excess emissions, leading to a reduction in Scope 2 GHG emissions from production.	MCTs provide real-time recommendations for optimizing production scheduling, load balancing, and resource usage. By reducing inefficiencies and minimizing unnecessary production runs, MCTs help cut energy consumption, which directly leads to a reduction in Scope 2 GHG emissions by improving overall operational efficiency.	Fully integrated MCTs autonomously manage production and logistics using AI-driven decisions. These continuous optimizations reduce energy consumption in real-time, leading to fewer GHG emissions. By ensuring energy is used efficiently, MCTs help reduce both Scope 2 emissions and indirect Scope 1 emissions (e.g., from fuel usage) across the manufacturing process.

EDDC	Digital Maturity Level				
	Descriptive	Diagnostic	Predictive	Prescriptive	Adaptive
	By providing visibility into OEE and defect rates, SPC helps operators track energy consumption patterns and identify inefficiencies in the process. While the direct effect on energy usage is small, the insights gained allow for more efficient energy management, contributing to Scope 2 emission reductions.	By diagnosing process inefficiencies and identifying variability, SPC helps reduce energy waste that results from inconsistent or suboptimal performance. Addressing these inefficiencies leads to a reduction in energy consumption, helping lower Scope 2 emissions by improving overall energy efficiency.	Predictive SPC capabilities allow for forecasting when processes are likely to drift or fail, helping to prevent unnecessary energy consumption. By predicting potential inefficiencies in advance, operators can take steps to optimize processes before excessive energy is used, leading to Scope 2 emission reductions.	SPC provides real-time recommendations to optimize process settings, minimizing the production of off-spec parts and reducing the need for rework. This reduces unnecessary production steps and excess energy consumption, contributing directly to Scope 2 emission reductions by optimizing energy use in the manufacturing process.	Fully integrated SPC systems autonomously adjust processes in real-time to maintain optimal conditions. By reducing variability and preventing the production of off-spec parts, SPC minimizes the need for rework and excessive production runs, leading to significant energy savings and reduced Scope 2 emissions.
	AR's visibility into real-time energy data helps operators identify inefficiencies in energy use, such as under-utilized machines or excess energy consumption. This visibility allows for better management of energy resources, leading to reductions in overall energy use and Scope 2 emissions.	AR helps identify the root causes of energy waste, such as faulty equipment or inefficient processes, by analyzing real-time data. By diagnosing these issues early, AR enables operators to take corrective actions that reduce unnecessary energy consumption, leading to Scope 2 emissions reductions.	AR's predictive capabilities allow for the anticipation of potential energy spikes or inefficiencies. By forecasting where energy use could increase, operators can take proactive measures to adjust processes before excess energy is consumed, contributing to Scope 2 emissions reductions.	AR provides real-time guidance to operators on how to adjust processes to be more energy-efficient. These actionable instructions ensure that operators perform tasks in ways that minimize energy consumption, directly contributing to Scope 2 emissions reductions by ensuring energy is used efficiently across the operation.	Fully integrated AR systems autonomously adjust workflows in real-time based on energy data, continuously optimizing operations to ensure that energy is used in the most efficient way. These continuous adjustments help minimize energy waste, resulting in significant Scope 2 emissions reductions by improving overall energy efficiency.
E2-4	DCS provide visibility into real-time process data, enabling operators to detect fluctuations that may lead to off-spec runs, preventing energy waste from overrun situations that would require venting or fuel burning, thus reducing emissions.	DCS help operators diagnose issues by analyzing process data for deviations that could lead to instability or off-spec production, enabling timely corrective actions that reduce the risk of waste fuel burning and chemical venting, lowering emissions.	DCS predict process instability or off-spec conditions before they occur, using trend analysis to provide alerts for proactive adjustments, preventing the need for fuel burning or venting during production, thereby reducing emissions.	DCS provide actionable recommendations to optimize processes, reducing the chances of off-spec production and unnecessary waste disposal, such as venting chemicals or burning excess fuel, thus lowering associated emissions.	DCS autonomously adjust process conditions to maintain stability and prevent off-spec production, continuously optimizing energy use, and minimizing the need for overrun situations that could lead to burning fuel or chemicals, significantly reducing emissions.

E2C	Digital Maturity Level				
	Descriptive	Diagnostic	Predictive	Prescriptive	Adaptive
	N/A	N/A	N/A	APC ensures that chemical processes run at optimal setpoints, preventing incomplete reactions and accidental releases of volatile compounds. By maintaining stability, APC reduces the risk of air emissions and pollutant releases, minimizing environmental impact and improving air quality.	Self-learning MPC enables APC to continuously optimize chemical processes, ensuring that reactions remain stable and efficient. This prevents off-spec batches and minimizes the need for flaring or venting, reducing both fuel waste and pollutant emissions.
	SPC provides real-time visibility into emissions data, enabling operators to identify abnormal emissions patterns early. While the focus at this level is on monitoring, it helps identify issues before they escalate, ensuring compliance with regulatory limits and reducing environmental impact.	SPC helps diagnose the causes of abnormal emissions by analyzing data and identifying process deviations. By understanding where emissions are coming from, operators can take corrective actions to prevent regulatory exceedances, ensuring compliance and minimizing the environmental impact of production processes.	SPC uses predictive capabilities to forecast potential emissions spikes before they occur. By anticipating these issues, operators can adjust processes to avoid regulatory exceedances, ensuring that emissions are kept within compliance limits and preventing environmental damage.	SPC provides actionable recommendations to adjust process parameters in real time, helping reduce emissions and stay within regulatory limits. These adjustments prevent excess emissions and ensure compliance with environmental regulations, promoting sustainability in manufacturing operations.	Fully integrated SPC systems autonomously adjust processes in real time to maintain emissions within acceptable limits. This continuous adaptation helps prevent regulatory exceedances and ensures that emissions are kept within compliance, contributing to sustainable manufacturing practices and reducing environmental impact.
E2-5	ERP provides real-time data on raw materials and product usage, improving traceability and enabling more precise control over hazardous substances, thereby reducing unnecessary consumption of hazardous chemicals.	ERP analyzes production data to identify inefficiencies, such as excess consumption of hazardous chemicals or raw materials, helping companies to minimize waste and optimize material usage.	ERP predicts material and chemical consumption in different production scenarios, allowing companies to plan and optimize material usage, thereby reducing unnecessary hazardous chemical consumption.	ERP generates production plans that are designed to minimize the consumption of hazardous substances by using raw materials more efficiently and reducing waste, contributing to safer production processes and a lower environmental impact.	ERP automatically adjusts production processes based on real-time data, ensuring the consumption of hazardous chemicals is minimized and production is more sustainable by reducing excess usage and waste.
	MES enables basic visibility of product traceability and material usage, helping to identify off-spec production and areas where hazardous materials may be misapplied, reducing the risk of hazardous waste generation.	MES identifies inefficiencies and quality issues, such as off-spec products or improper hazardous material usage, helping to reduce the need for rework and limiting hazardous waste generation by enabling corrective actions.	MES uses predictive analytics to foresee potential defects or misapplications of hazardous materials, enabling operators to adjust processes ahead of time, reducing waste and minimizing the risk of spills or misapplications.	MES generates optimized production schedules and material usage plans, reducing off-spec products, minimizing rework, and ensuring hazardous materials are used efficiently, thus preventing hazardous waste and limiting scrap generation.	MES dynamically adjusts production processes in real time to minimize off-spec production, prevent hazardous material misapplication, and reduce overproduction, ensuring less hazardous waste is generated while improving resource utilization.

EDDC	Digital Maturity Level				
	Descriptive	Diagnostic	Predictive	Prescriptive	Adaptive
	IIoT systems provide real-time monitoring of machine and process conditions, allowing operators to detect early signs of potential equipment failures or process deviations. Early detection helps minimize the risk of producing off-spec materials, thus reducing the generation of hazardous waste.	By diagnosing patterns and anomalies in real-time data, IIoT systems help pinpoint areas where processes are deviating from optimal conditions, preventing the production of off-spec materials and reducing hazardous waste generation by enabling corrective actions.	IIoT systems predict potential failures or process deviations by analyzing historical and real-time data. Predictive capabilities allow for preemptive maintenance or adjustments, which helps avoid producing off-spec materials and reduces hazardous waste generation.	IIoT systems provide actionable recommendations to adjust machine parameters or process conditions in real-time. These adjustments help ensure that processes stay within specification, reducing the need for rework or disposal of off-spec materials and minimizing hazardous waste generation.	Fully integrated IIoT systems with adaptive algorithms autonomously adjust processes and machine operations to keep conditions within optimal ranges, preventing the production of off-spec materials. This reduces the need for rework and lowers hazardous waste generation without requiring human intervention.
	By collecting real-time data, edge devices provide visibility into the production process, allowing operators to monitor conditions that could lead to off-spec batches. This early detection helps to avoid the production of contaminated or off-spec materials, minimizing the need for scrapping or hazardous material treatment.	Edge devices analyze data locally to detect deviations, such as equipment operating outside optimal conditions. These diagnostics enable operators to take immediate corrective actions, preventing off-spec production and reducing the amount of material that needs to be scrapped or treated.	Edge devices use predictive models to forecast potential deviations or issues in real-time, such as abnormal temperature or pressure changes. By anticipating these issues, operators can take preemptive corrective actions to prevent off-spec production, thus reducing the amount of hazardous material that needs to be disposed of or treated.	Edge devices provide real-time recommendations and adjustments to process parameters, ensuring that machines stay within optimal operating conditions. These corrections prevent off-spec batches, minimizing the need to scrap or treat hazardous materials and improving overall process efficiency.	Fully integrated edge devices with local AI agents autonomously adjust machine operations to optimize quality in real-time. By continuously monitoring and correcting process conditions, these devices prevent off-spec production and minimize hazardous material waste without the need for manual intervention, contributing to more sustainable manufacturing practices.
	Data historians enable manufacturers to visualize historical process data, allowing them to detect trends and deviations that could lead to off-spec batches. Early identification of these deviations helps to prevent the production of hazardous scrap, reducing material waste.	Data historians help diagnose past operational issues and trends, identifying where process drifts occurred that led to off-spec production. This enables corrective actions that prevent the generation of hazardous scrap, contributing to a more sustainable and efficient production process.	By leveraging historical data, data historians support predictive models that can anticipate process deviations. These models help identify when a process is about to go out of specification, allowing for corrective measures before off-spec batches are produced, thus reducing hazardous scrap and improving material efficiency.	Data historians provide integrated data to optimization engines, which make recommendations for real-time adjustments to process variables. These prescriptive actions help keep production within specification, minimizing the production of off-spec batches and reducing the need for hazardous material treatment or disposal.	In fully integrated systems, data historians stream real-time data to adaptive machine learning models, which autonomously adjust operations to correct process drifts in real time. This continuous, autonomous optimization prevents off-spec production, reducing hazardous scrap and ensuring material efficiency.

EDDC	Digital Maturity Level				
	Descriptive	Diagnostic	Predictive	Prescriptive	Adaptive
	By monitoring key quality metrics, SPC provides early visibility into production performance and potential issues. This allows operators to identify potential process drifts or deviations before they lead to off-spec products or hazardous waste, thus helping to reduce waste generation.	SPC's diagnostic capabilities allow for deeper analysis of variability, pinpointing the causes of defects or malfunctions early. By identifying issues that may lead to off-spec products, operators can take corrective actions to prevent the generation of hazardous waste, reducing waste and improving process sustainability.	Predictive SPC capabilities enable forecasting of process drift or equipment failures that could lead to defects. By anticipating these issues, operators can take proactive actions to reduce off-spec production and prevent defective products from being generated, minimizing the need for hazardous waste disposal.	SPC provides real-time recommendations to adjust process parameters to maintain product quality and reduce defects. These adjustments help minimize the likelihood of generating off-spec products, thus reducing the need for hazardous waste disposal and improving overall sustainability in production.	Fully automated SPC systems continuously adjust processes in real-time to maintain quality. By autonomously rejecting out-of-spec parts or adjusting the process, SPC minimizes the generation of off-spec products and hazardous waste, significantly reducing material waste and improving sustainability.
E5-4	MES provides visibility into material usage and production status, helping identify areas where raw materials may be overused or misallocated, preventing unnecessary material waste, especially for expensive high-tech components.	MES analyzes data to identify inefficiencies in material usage, helping pinpoint when and where excess materials are being used, thus minimizing raw material waste and preventing overproduction.	MES forecasts material needs and production demand, enabling more precise material allocation and just-in-time manufacturing to avoid overproduction and the resulting waste, ensuring that expensive materials are used efficiently.	MES generates optimized production plans that ensure raw materials, particularly expensive high-tech components, are used efficiently, enforcing just-in-time manufacturing to reduce raw material overuse and prevent scrapping of critical components.	MES dynamically adjusts production processes and material usage based on real-time data, ensuring just-in-time manufacturing is maintained, raw material waste is minimized, and critical components are not scrapped.
	MCTs track the use of raw materials and energy across production processes, helping identify inefficiencies. By providing real-time insights, MCTs help optimize material and energy usage, reducing waste and improving overall resource efficiency, directly contributing to reducing resource intensity.	MCTs diagnose inefficiencies in raw material and energy usage by analyzing integrated data. By identifying causes of waste or suboptimal usage, MCTs allow for corrective actions that optimize material and energy consumption, reducing resource intensity and improving overall sustainability.	By forecasting potential resource shortages or inefficiencies, MCTs help prevent overuse of raw materials and energy. These predictive capabilities enable better resource planning, reducing waste and optimizing usage, thereby lowering resource intensity and contributing to more sustainable operations.	MCTs provide real-time recommendations to optimize production scheduling and material usage. By balancing workloads across production lines and enabling the reuse of outputs, MCTs help reduce raw material and energy consumption, directly contributing to goals of reducing resource intensity.	Fully integrated MCTs use real-time AI-driven decisions to autonomously adjust operations, balancing workloads and ensuring more efficient use of raw materials and energy. These continuous adjustments improve overall resource efficiency and reduce resource intensity by ensuring that materials and energy are used optimally.

EDDC	Digital Maturity Level				
	Descriptive	Diagnostic	Predictive	Prescriptive	Adaptive
	By displaying assembly sequences and material requirements, AR helps ensure that the correct amount of material is used at each stage of production. This helps reduce the risk of material overconsumption by providing operators with real-time information about what is needed for each task, promoting material efficiency.	AR overlays allow operators to identify when too much material is being used or when parts are incorrectly assembled. By diagnosing these issues in real time, AR helps reduce material waste and ensures that only the right amount of material is consumed, preventing overconsumption and waste.	AR can predict where material overconsumption might happen by simulating the assembly process. By anticipating inefficiencies in material usage, AR enables operators to adjust processes before excess material is used, minimizing waste and ensuring that only the necessary amount of material is consumed during production.	AR provides real-time, step-by-step instructions on how to assemble parts optimally. These instructions help ensure that the right amount of material is used at each stage of the process, reducing the risk of material overconsumption and waste by guiding operators through the most efficient procedures.	Fully integrated AR systems autonomously adapt the assembly process in real-time, ensuring that material usage remains optimal. By adjusting the sequence or material requirements dynamically, AR minimizes the risk of overconsumption and waste, improving overall material efficiency and contributing to more sustainable manufacturing.
E5-5	ERP provides real-time tracking of material usage and production yields, giving visibility into where inefficiencies, such as excessive scrap or hazardous waste, occur.	ERP analyzes production data to identify causes of inefficiencies, such as high yield loss or scrap generation, enabling businesses to pinpoint areas where waste can be reduced.	ERP uses predictive models to forecast production outcomes, helping to anticipate yield losses or scrap generation in advance, allowing for corrective actions to be taken before waste occurs.	ERP generates production plans that focus on minimizing waste by optimizing material use, improving yield, and preventing excessive scrap, contributing to a reduction in hazardous waste.	ERP automatically adjusts production processes based on real-time data, ensuring minimal waste generation and optimized material usage, significantly reducing scrap and hazardous waste.
	APS allows for basic tracking of material usage, line changeovers, and production runs, offering insights into areas where excess material waste or inefficiencies may occur.	APS identifies patterns of waste, such as frequent line changeovers and production errors, highlighting opportunities for improvement and the reduction of both hazardous and non-hazardous waste.	APS predicts potential inefficiencies in material usage, such as excessive waste or off-spec products, enabling companies to adjust schedules and minimize waste before it occurs.	APS generates optimized production schedules that reduce the frequency of line changeovers, lowering the likelihood of errors, rework, and waste, while improving material utilization and minimizing both hazardous and non-hazardous waste.	APS autonomously adjusts production schedules to reduce material waste and minimize hazardous waste, ensuring optimal resource allocation, reducing the need for rework, and eliminating errors that can lead to waste generation.
	MES captures production counts, scrap, and defect data, enabling basic visibility into material losses and highlighting overproduction risks.	MES aggregates yield and defect reports by machine or process, identifying key waste contributors and allowing focused interventions to minimize defective output and unnecessary material use.	MES predicts scrap risks and overproduction based on historical patterns, enabling proactive adjustments to reduce material waste and support just-in-time production.	MES recommends adjustments to production schedules, sequencing, or preventive maintenance to reduce the risk of scrap, overproduction, and inefficient material use, supporting minimal-waste operations.	MES dynamically reschedules production in real time based on shop floor state, minimizing overproduction, aligning runs with demand, and ensuring materials are consumed with maximum efficiency and minimal waste.

ECDC	Digital Maturity Level				
	Descriptive	Diagnostic	Predictive	Prescriptive	Adaptive
	PLCs provide precision in task automation, reducing the likelihood of human error in processes that involve hazardous consumables, such as etchants and gases, minimizing the risk of mis-dosing and reducing material waste.	PLCs help identify deviations in material use, such as overuse of etchants or gases, and excessive scrap generation, providing insights into areas where precision can be improved to minimize waste and improve material efficiency.	PLCs predict potential issues like mis-dosing of hazardous materials or increased scrap based on historical data and trends, allowing for adjustments before waste or errors occur, contributing to reduced consumption of hazardous materials.	PLCs generate optimized process parameters to ensure accurate material use, reducing the chances of producing off-spec parts and helping to avoid wastage of hazardous consumables like etchants and gases by ensuring precise dosing.	PLCs autonomously adjust process parameters in real-time to ensure that materials, particularly hazardous consumables, are used efficiently and that scrap is minimized, reducing waste and improving sustainability in manufacturing.
	IIoT systems provide real-time monitoring of machine and process conditions, allowing operators to detect early signs of potential equipment failures or process deviations. Early detection helps minimize the risk of producing off-spec materials, thus reducing the generation of hazardous waste.	By diagnosing patterns and anomalies in real-time data, IIoT systems help pinpoint areas where processes are deviating from optimal conditions, preventing the production of off-spec materials and reducing hazardous waste generation by enabling corrective actions.	IIoT systems predict potential failures or process deviations by analyzing historical and real-time data. Predictive capabilities allow for preemptive maintenance or adjustments, which helps avoid producing off-spec materials and reduces hazardous waste generation.	IIoT systems provide actionable recommendations to adjust machine parameters or process conditions in real-time. These adjustments help ensure that processes stay within specification, reducing the need for rework or disposal of off-spec materials and minimizing hazardous waste generation.	Fully integrated IIoT systems with adaptive algorithms autonomously adjust processes and machine operations to keep conditions within optimal ranges, preventing the production of off-spec materials. This reduces the need for rework and lowers hazardous waste generation without requiring human intervention.
	By collecting real-time data, edge devices provide visibility into the production process, allowing operators to monitor conditions that could lead to off-spec batches. This early detection helps to avoid the production of contaminated or off-spec materials, minimizing the need for scrapping or hazardous material treatment.	Edge devices analyze data locally to detect deviations, such as equipment operating outside optimal conditions. These diagnostics enable operators to take immediate corrective actions, preventing off-spec production and reducing the amount of material that needs to be scrapped or treated.	Edge devices use predictive models to forecast potential deviations or issues in real-time, such as abnormal temperature or pressure changes. By anticipating these issues, operators can take preemptive corrective actions to prevent off-spec production, thus reducing the amount of hazardous material that needs to be disposed of or treated.	Edge devices provide real-time recommendations and adjustments to process parameters, ensuring that machines stay within optimal operating conditions. These corrections prevent off-spec batches, minimizing the need to scrap or treat hazardous materials and improving overall process efficiency.	Fully integrated edge devices with local AI agents autonomously adjust machine operations to optimize quality in real-time. By continuously monitoring and correcting process conditions, these devices prevent off-spec production and minimize hazardous material waste without the need for manual intervention, contributing to more sustainable manufacturing practices.

CDC	Digital Maturity Level				
	Descriptive	Diagnostic	Predictive	Prescriptive	Adaptive
	Data historians enable manufacturers to visualize historical process data, allowing them to detect trends and deviations that could lead to off-spec batches. Early identification of these deviations helps to prevent the production of hazardous scrap, reducing material waste.	Data historians help diagnose past operational issues and trends, identifying where process drifts occurred that led to off-spec production. This enables corrective actions that prevent the generation of hazardous scrap, contributing to a more sustainable and efficient production process.	By leveraging historical data, data historians support predictive models that can anticipate process deviations. These models help identify when a process is about to go out of specification, allowing for corrective measures before off-spec batches are produced, thus reducing hazardous scrap and improving material efficiency.	Data historians provide integrated data to optimization engines, which make recommendations for real-time adjustments to process variables. These prescriptive actions help keep production within specification, minimizing the production of off-spec batches and reducing the need for hazardous material treatment or disposal.	In fully integrated systems, data historians stream real-time data to adaptive machine learning models, which autonomously adjust operations to correct process drifts in real time. This continuous, autonomous optimization prevents off-spec production, reducing hazardous scrap and ensuring material efficiency.
	Digital twins provide a detailed visualization of current processes and materials, helping manufacturers identify points in the process where changes could lead to defective outputs or hazardous scrap. This insight allows for adjustments before physical changes are made, reducing waste generation.	By simulating potential fault scenarios and diagnosing how material or process changes might lead to defects, digital twins help manufacturers identify and correct issues before they result in hazardous scrap. Early detection reduces waste by ensuring that processes remain within acceptable quality standards.	Digital twins allow manufacturers to predict the impact of changes in real-time, such as adjusting materials or process parameters. By forecasting potential defects or issues before they occur, digital twins help prevent the production of off-spec products and reduce the amount of hazardous scrap generated.	By providing recommendations based on real-time data, digital twins suggest optimal process parameters that minimize the risk of defective outputs. These adjustments help avoid generating hazardous scrap by keeping processes within ideal operating conditions, ensuring that production remains efficient and waste is minimized.	Fully integrated digital twins with real-time adaptive capabilities autonomously adjust processes to maintain quality and prevent deviations that might result in defective or off-spec outputs. This continuous optimization ensures that hazardous scrap generation is minimized by keeping the production process within optimal conditions.
	N/A	N/A	N/A	APC optimizes process variables in real-time to reduce variability, ensuring that production runs are more stable. This reduction in variability leads to fewer off-spec products and rejections, directly reducing scrap and material waste.	Self-learning MPC allows APC to adjust parameters dynamically, ensuring that equipment operates at peak efficiency. This minimizes variability and reduces the number of rejected batches, improving overall equipment effectiveness (OEE) and decreasing raw material waste by reducing the number of runs needed to achieve the desired output.

CDC	Digital Maturity Level				
	Descriptive	Diagnostic	Predictive	Prescriptive	Adaptive
	By providing real-time monitoring of production metrics, SPC helps identify deviations in process conditions that could lead to off-spec material or defects. Early identification reduces the likelihood of producing off-spec batches, preventing waste generation and minimizing the risk of hazardous waste disposal.	SPC's diagnostic tools help identify the root causes of variability, such as machine malfunctions or suboptimal process conditions. By diagnosing these issues early, SPC helps prevent the creation of off-spec material, reducing scrap and rework and preventing hazardous waste generation.	Predictive SPC capabilities forecast potential process drift or equipment failures that could lead to off-spec products. By taking proactive measures, operators can adjust processes before defects occur, reducing the formation of defective batches, minimizing scrap, and preventing hazardous waste generation.	SPC recommends real-time adjustments to optimize process parameters, ensuring that production stays within desired quality specifications. These adjustments prevent the creation of off-spec material, thereby reducing the need for scrap and rework, which directly lowers waste generation and helps minimize the impact of hazardous waste.	Fully integrated SPC systems autonomously adjust control parameters in real-time, ensuring that processes remain stable and within specification. By preventing the creation of off-spec batches and rejecting defective products automatically, SPC reduces scrap, rework, and overall waste generation, contributing to more sustainable production practices.
	By providing clear, visual instructions, AR reduces the risk of assembly errors. Accurate assembly reduces the number of defective parts and minimizes scrap, improving resource efficiency and reducing waste in the manufacturing process.	AR helps diagnose defects early in the assembly process by overlaying real-time data on parts or assemblies. Early detection of errors prevents defective parts from advancing further in the process, minimizing the need for rework and scrap.	AR's predictive capabilities help identify potential defects before they occur by simulating the assembly process. By predicting where errors might happen, operators can take proactive steps to avoid defective products, significantly reducing scrap and rework.	AR offers real-time, optimized instructions that guide operators through the most efficient assembly process. By reducing the chance of mistakes, AR helps to prevent defective parts and unnecessary rework, directly minimizing scrap generation.	Fully integrated AR systems autonomously adjust the assembly process in real-time, detecting and correcting errors before they result in defects. This continuous optimization ensures high-quality assembly, preventing scrap generation and reducing waste from defective products.
S1-9	AR supports employees with cognitive impairments by providing visual and interactive guidance on complex tasks. This functionality promotes diversity by helping employees who might otherwise struggle with these tasks, supporting a more inclusive and accessible workplace.	AR assists employees with disabilities by diagnosing difficulties they might face in completing tasks. For example, employees with visual impairments can receive high-contrast overlays or tactile feedback. This helps employees understand where adjustments are needed, promoting accessibility and inclusivity in the workplace.	AR predicts when employees with cognitive, visual, or physical impairments may face challenges in task execution and provides solutions such as audio-guided instructions, gaze tracking, or voice command suggestions. This proactive approach ensures that employees are supported before encountering difficulties, enhancing accessibility and ensuring equal participation in the workplace.	AR adapts work instructions to meet the individual needs of employees with disabilities, offering tailored solutions like voice commands for those with mobility impairments or high-contrast visual cues for employees with visual impairments. These prescriptive adjustments ensure that employees can perform tasks efficiently and independently, promoting a more diverse and inclusive work environment.	Fully integrated AR systems autonomously adjust guidance and assistive features in real-time, responding to the needs of employees with disabilities. By adapting to individual requirements, such as adjusting for visual impairments or mobility limitations, AR ensures that every employee can complete their tasks efficiently, supporting an inclusive, accessible, and diverse workplace.

CDC	Digital Maturity Level				
	Descriptive	Diagnostic	Predictive	Prescriptive	Adaptive
S1-13	HMI systems provide intuitive, user-friendly interfaces that improve accessibility, reducing cognitive overload and allowing operators to focus on essential tasks, leading to improved work efficiency and satisfaction.	HMI systems offer diagnostic features that help operators identify inefficiencies in real-time through easy-to-understand visualizations, which enhances decision-making and reduces stress, ultimately improving worker productivity and job satisfaction.	HMI systems offer predictive capabilities through alerts and trend analysis, reducing the cognitive load on operators by informing them about potential issues in advance, which helps improve work satisfaction by reducing surprises and enabling proactive actions.	HMI systems provide actionable suggestions and process optimizations, reducing the complexity of decision-making for operators and improving their efficiency and comfort, thus boosting productivity and work satisfaction.	N/A
	By enabling remote access and collaboration, cloud storage allows for more flexible work arrangements, improving work-life balance and enabling inclusion across diverse teams. This contributes to better working conditions and encourages sustainable working practices.	Cloud-based storage helps teams collaborate more effectively across different sites, sharing insights and diagnosing operational issues. This reduces the need for travel, which supports inclusivity by enabling diverse teams to contribute without geographical barriers.	With predictive analytics, cloud-based storage allows teams to collaborate on forecasting operational challenges and energy consumption patterns. This collaborative approach promotes more sustainable decision-making by bringing together insights from various teams and locations, improving inclusivity.	Cloud integrates with multi-site analytics to recommend tailored training programs, collaborative tools, or knowledge-sharing initiatives, improving worker inclusion and development.	Cloud-edge systems adaptively coordinate cross-factory knowledge flows, ensuring workers everywhere get real-time access to the right training and support tools, improving job satisfaction and inclusion without manual intervention.
	AR helps upskill workers by providing clear, step-by-step instructions, enhanced with foreign-language overlays, making it easier for workers from diverse linguistic backgrounds to understand tasks. This promotes inclusion, making it possible for workers to perform tasks efficiently, regardless of their language or previous training.	AR assists in diagnosing training gaps by analyzing task performance in real-time. Workers can receive immediate feedback and follow up with supplementary training, which helps them overcome language or skill barriers and improves overall workforce inclusion by ensuring that everyone is equipped to succeed.	AR predicts when workers might struggle with task comprehension, especially if language barriers exist. By offering proactive support in the form of foreign-language overlays or additional visual aids, AR helps workers prepare for and overcome challenges, facilitating faster learning and more inclusive training.	AR delivers real-time, tailored instructions with foreign-language overlays, ensuring that training is relevant to each worker's needs. By adapting to the worker's progress and providing language-specific guidance, AR ensures that all workers, regardless of background, receive the support they need to quickly learn and execute tasks, promoting inclusion and workforce diversity.	Fully integrated AR systems autonomously adjust training content in real-time, offering language-specific support and modifying visual guidance to match the worker's pace and understanding. This adaptability helps workers of all linguistic backgrounds quickly acquire new skills, enhancing diversity and inclusion by ensuring everyone has access to effective training.

CDC	Digital Maturity Level				
	Descriptive	Diagnostic	Predictive	Prescriptive	Adaptive
S1-14	By tracking real-time data on machine conditions and operational performance, MCTs help identify safety hazards and equipment malfunctions early. This visibility allows for quick interventions, reducing the likelihood of workplace accidents and promoting a safer working environment.	MCTs diagnose issues in real-time by analyzing integrated data, such as identifying patterns of failure or wear that could lead to accidents. By pinpointing the root causes of potential safety hazards, MCTs enable timely maintenance and corrective actions, improving worker safety and reducing health risks.	By predicting potential machine failures or unsafe conditions before they occur, MCTs enable proactive maintenance. This reduces the risk of accidents or health issues related to equipment malfunctions, creating a safer workplace by addressing risks before they escalate.	MCTs provide real-time recommendations for maintenance actions, such as equipment servicing or process adjustments, to prevent safety hazards and reduce the likelihood of accidents. By optimizing machine conditions, MCTs help create a safer work environment and minimize health risks for employees.	Fully integrated MCTs autonomously adjust operations in real-time to ensure that machines and processes remain safe and within operational limits. By making these adjustments automatically, MCTs prevent the occurrence of unsafe conditions and protect worker health, supporting a safer and more efficient workplace.
	By monitoring machinery performance, including vibrations, SPC helps detect early signs of wear and tear that could lead to equipment failure. This proactive monitoring helps identify potential safety hazards, contributing to a safer working environment and reducing the risk of incidents.	SPC's diagnostic tools help identify unusual patterns in process data, such as spikes in machinery vibration. By diagnosing these issues early, SPC allows for timely maintenance or adjustments, reducing the likelihood of equipment failure and preventing safety incidents in the workplace.	SPC's predictive capabilities enable operators to forecast potential failures in machinery, such as worn-out components or abnormal vibrations that could lead to safety hazards. By anticipating these issues, proactive maintenance can be scheduled, preventing accidents and ensuring a safer work environment.	SPC provides actionable recommendations based on real-time data to address machinery issues, such as excessive vibration. By recommending timely maintenance or adjustments, SPC helps prevent incidents that could endanger workers, promoting a safer workplace environment.	Fully integrated SPC systems autonomously adjust machine operations in real-time, such as by shutting down machinery or altering process parameters when excessive vibrations are detected. This automated response ensures that machinery operates safely, preventing accidents and protecting worker health and safety.
	By providing clear visual instructions and real-time safety alerts, AR helps workers perform tasks more accurately and avoid hazardous areas. This reduces the risk of human error, enhancing safety and supporting a safer work environment for all employees, especially in complex or high-risk manufacturing settings.	AR helps diagnose potential safety risks by analyzing worker actions and alerting them to unsafe behaviors. By providing real-time feedback and hazard detection, AR helps reduce the likelihood of accidents and unsafe conditions, improving overall workplace safety and reducing human error.	Using predictive capabilities, AR can forecast when workers are likely to enter hazardous zones or make unsafe decisions. By providing proactive safety instructions or alerts, AR helps avoid dangerous situations before they occur, enhancing overall safety and reducing the risk of injuries in the workplace.	AR provides prescriptive guidance by recommending real-time adjustments to task execution, ensuring workers stay out of hazardous zones and avoid potential collisions. These real-time instructions not only reduce human error but also help create a safer work environment, promoting both individual and collective safety.	Fully integrated AR systems autonomously adjust to the worker's real-time actions and the environment. By continuously updating safety guidelines, issuing live equipment data, and offering hazard warnings, AR ensures a dynamic, real-time response to emerging safety concerns, minimizing human error and improving overall workplace safety. Additionally, emotion-sensing tools help monitor worker well-being, promoting a safer and more inclusive environment.

EDDC	Digital Maturity Level				
	Descriptive	Diagnostic	Predictive	Prescriptive	Adaptive
S1-15	MES provides visibility into workforce data, allowing managers to monitor employee work hours and identify potential overtime or work schedule issues, helping ensure better work-life balance and compliance with labor regulations.	MES aggregates data on employee hours and shift patterns, enabling managers to diagnose issues like overtime accumulation or irregular shift patterns, which can be corrected to avoid excessive working hours and improve employee well-being.	MES uses predictive analytics to forecast potential overtime or work-life balance issues, enabling proactive adjustments to workforce scheduling and preventing excessive working hours before they occur.	MES suggests optimized scheduling changes or sends automatic alerts when employees approach overtime thresholds, ensuring better work-life balance, regulatory compliance, and reducing the risk of worker fatigue or burnout.	MES autonomously adjusts shift schedules in real time based on production needs and workforce availability, ensuring that employees do not exceed overtime limits while optimizing labor efficiency and promoting better work-life balance.
	HMI systems provide real-time monitoring of workload and cognitive load, allowing workers to see their own stress levels, helping them manage pacing and reducing cognitive overload, which contributes to maintaining a healthy work-life balance.	HMI systems analyze real-time data to diagnose signs of cognitive overload or fatigue in workers, allowing for timely interventions like suggesting rest breaks, which supports worker well-being and ensures sustainable productivity over time.	HMI systems use predictive analytics to forecast when workers are approaching cognitive overload or fatigue, providing advanced alerts for rest breaks to prevent burnout and ensure long-term worker health and productivity.	HMI systems offer actionable suggestions for pacing and rest periods based on real-time data, helping workers balance their workloads and reduce stress, which enhances work-life balance and supports long-term health and productivity.	N/A
	Digital twins offer operators real-time visibility into machine performance, enabling them to make informed decisions remotely. This reduces the need for on-site presence and commuting, contributing to improved work-life balance while maintaining effective operations.	By simulating and diagnosing potential operational issues, digital twins enable remote troubleshooting and maintenance. This reduces the need for physical presence on-site, supporting work-life balance and reducing commuting while ensuring timely maintenance.	With predictive capabilities, digital twins allow operators to anticipate issues and take remote actions before they occur. This proactive approach reduces the need for emergency on-site maintenance visits, enhancing work-life balance by decreasing commuting requirements and optimizing maintenance schedules.	Digital twins not only suggest real-time optimizations but also enable operators to make adjustments remotely. This reduces the need for on-site maintenance visits, improving work-life balance and allowing operators to address issues efficiently without commuting.	Fully integrated digital twins autonomously adjust operational parameters and synchronize physical and virtual environments. This allows operators to monitor and control systems remotely in real-time, significantly reducing the need for on-site visits and improving work-life balance by minimizing commuting requirements.

CDC	Digital Maturity Level				
	Descriptive	Diagnostic	Predictive	Prescriptive	Adaptive
	AR enables technicians to receive remote assistance for maintenance tasks, reducing the need for on-site presence. By sharing their field of view with remote experts, technicians can perform repairs efficiently, saving time and eliminating the need for commuting, which improves work-life balance.	AR supports technicians in diagnosing equipment issues without needing to be on-site. By connecting with remote experts, technicians can receive diagnostic support and perform repairs, improving work-life balance by eliminating the commute while ensuring equipment is maintained efficiently.	Using AR, remote maintenance technicians can predict when equipment is likely to fail and provide real-time solutions to prevent breakdowns. This predictive capability reduces the need for emergency on-site visits, which lowers the frequency of commuting and allows technicians to manage their time better, enhancing work-life balance.	AR offers prescriptive guidance to technicians by overlaying step-by-step maintenance instructions, which allows them to perform repairs with greater precision. By performing tasks remotely and without the need for physical presence, AR contributes to improved work-life balance for technicians, saving time and energy spent on commuting.	Fully integrated AR systems autonomously adjust to the maintenance environment in real-time, ensuring that technicians can perform repairs without needing to travel to the factory. This reduces commuting and enhances work-life balance by enabling technicians to access expert support remotely and complete their tasks efficiently from any location.
G1-1	MES enables the logging of safety incidents and near-misses directly from the shop floor, offering transparency and initial documentation of safety issues, helping promote a culture of safety and accountability.	MES analyzes reported incidents and near-misses, helping identify recurring safety issues or problematic areas, allowing managers to diagnose and address underlying safety risks to improve overall workplace safety.	MES leverages predictive analytics to forecast high-risk areas or potential incidents based on historical safety data, enabling managers to take proactive measures and mitigate safety risks before they escalate.	MES generates recommendations for safety improvements and process changes based on the analysis of reported incidents, guiding management on how to reduce workplace hazards and improve safety protocols.	MES autonomously reacts to safety incidents or near-misses in real time, triggering alerts or stopping production to prevent accidents, ensuring immediate response to risks, while maintaining transparency and ethical behavior.
	HMI systems enable operators to easily report safety issues in real-time, improving hazard identification and ensuring quick communication of unsafe conditions, thereby supporting a safer workplace and reducing the risk of accidents or environmental harm.	HMI systems analyze reported safety incidents to identify recurring hazards or unsafe conditions, helping prioritize areas for improvement and enabling a safer environment, which ultimately reduces safety-related incidents and the impact on workers' health and safety.	HMI systems predict future safety risks by analyzing trends in reported hazards, providing proactive alerts to prevent accidents before they occur, enhancing workplace safety and contributing to a more sustainable working environment.	HMI systems recommend process improvements or corrective actions based on reported hazards, helping to reduce the occurrence of unsafe conditions and improve overall safety, which reduces risk to workers and supports a healthier, safer workplace.	N/A

ESRS	Digital Maturity Level				
	Descriptive	Diagnostic	Predictive	Prescriptive	Adaptive
	MCTs enhance transparency by offering real-time visibility into all aspects of production, making it easier for stakeholders to understand operational practices. This openness supports an ethical corporate culture by ensuring accountability and encouraging ethical decision-making at all levels.	By diagnosing issues across processes, MCTs make it possible to track the causes of inefficiencies or mistakes in real time. This ability to trace and identify problem areas increases accountability, as decisions can be made based on transparent data, promoting ethical behavior and transparency in operations.	MCTs predict operational issues, such as supply shortages or equipment failures, allowing organizations to act proactively. This predictive capability ensures that ethical decisions are made in advance to prevent harm, promote responsible practices, and enhance transparency throughout the process.	MCTs offer recommendations for real-time adjustments to improve operational efficiency. These recommendations can be aligned with ethical standards, ensuring that decisions are made responsibly, reducing waste, and promoting sustainability and transparency in business operations.	Fully integrated MCTs autonomously adjust operations in real-time to ensure that processes are aligned with ethical guidelines. These systems make continuous adjustments based on data, ensuring transparency and accountability, which supports an ethical corporate culture where decisions are data-driven and integrity is maintained.

D.5. Maturity model development: KPIs identification

Table D.11: ESRS impact indicators with digital maturity levels for manufacturing technology.

ESRS impact	Maturity level	People	Process	Policy
E1-5		Digital energy consumption competency	Digital energy efficiency competency	Digital renewable energy competency
	Descriptive	Most employees have limited access to basic, historical energy consumption reports. Data is siloed and not actionable in real time.	Energy data is automatically collected at regular intervals from key systems and consolidated into dashboards or reports. The focus is on summarizing what happened in terms of total plant energy usage.	Basic energy policies are in place but rely on manual processes with no digital tools for tracking or enforcement.
	Diagnostic	Most staff regularly review energy usage dashboards, identify simple anomalies (e.g., unexpected spikes), and report them for further analysis.	Operators and engineers use real-time and historical data to analyze why energy consumption deviated from expected patterns. Tools support the identification of inefficiencies, equipment issues, or production anomalies that drive higher usage.	Policies require digital systems to monitor energy usage and provide diagnostic insights for identifying inefficiencies.
	Predictive	Most employees receive system-generated alerts forecasting potential energy overuse. These are integrated into shift planning and equipment scheduling.	Predictive models estimate total energy usage based on upcoming production schedules, environmental factors, and historical data, allowing proactive planning for peak demand periods or energy-saving opportunities.	Policies integrate predictive tools that forecast energy demand and support proactive planning based on data trends.
	Prescriptive	Advanced analytics systems recommend specific energy-saving actions (e.g., machine sequencing, temperature control adjustments), which are incorporated into daily routines.	Systems recommend or automatically implement adjustments, such as rescheduling energy-intensive tasks or optimizing machine settings, to reduce total energy usage while meeting production targets.	Policies mandate systems that automate energy-saving actions in real time, based on defined rules and operational data.

ESRS impact	Maturity level	People	Process	Policy
	Adaptive	Self-learning systems automatically optimize total energy consumption across processes. Employees intervene only for rare, complex exceptions or overrides.	The plant operates with fully autonomous energy optimization. AI systems continuously ingest live data and adjust production processes in real time to minimize energy consumption without human input.	Policies embed AI-driven systems that learn from operations and autonomously optimize energy use across the plant.
E1-6		Digital Scope 1 emissions competency	Digital Scope 1 emissions intelligence	Digital Scope 1 emissions policy integration
	Descriptive	Few employees are trained or actively using digital tools to track Scope 1 emissions. Data, if available, is siloed and retrospective, with minimal operational impact.	Scope 1 emissions data (e.g., fuel use, refrigerant leaks, process gas losses) is manually collected and reported post-process. Insights are typically delayed and reactive.	General Scope 1 emissions targets exist, but they are not connected to digital systems. Monitoring and reduction efforts are manual and reactive.
	Diagnostic	Targeted employees are trained to use dashboards and diagnostic tools (e.g., SCADA, MES) to identify sources of Scope 1 emissions. Monitoring is routine but mostly reactive.	Operators use diagnostic tools (e.g., SCADA alarms, sensor alerts) to detect abnormal usage of high-emission inputs and manually intervene to address issues such as excessive fuel burn or refrigerant use.	Digital audits are required to monitor Scope 1 emissions drivers, such as fuel use, refrigerants, and process gases, enabling diagnostics and performance reviews.
	Predictive	Staff respond to system-generated alerts and forecasts predicting potential Scope 1 emissions events. Preventive actions are taken during planning and operations.	Predictive analytics model expected Scope 1 emissions based on production plans, weather, and equipment condition. The system alerts teams to potential emissions peaks, enabling early planning and mitigation.	Policies require predictive models that forecast Scope 1 emissions based on operational plans and identify high-emission scenarios in advance.
	Prescriptive	Employees use prescriptive analytics and digital recommendations (e.g., optimal equipment settings, maintenance schedules) to minimize Scope 1 emissions as part of standard workflows.	Digital systems recommend specific operational changes (such as adjusting burner settings, switching cooling modes, or modifying process sequences) to proactively reduce Scope 1 emissions in real time.	Prescriptive control systems are used in real time to optimise operations and reduce Scope 1 emissions, based on defined thresholds and operational data.
	Adaptive	Employees actively contribute to continuous improvement platforms, sharing outcomes and insights that enhance adaptive digital systems managing Scope 1 emissions.	AI systems autonomously control combustion, cooling, heating, and other emissions-relevant processes in real time. They continuously optimize to minimize Scope 1 emissions while maintaining safety and performance, without requiring human intervention.	Policies mandate autonomous optimization of Scope 1 emissions, with AI-driven systems adjusting processes without manual input, while governance ensures oversight and validation.
E2-4		Digital air pollutant emissions competency	Digital process air pollutant emissions intelligence	Digital air pollutant emissions policy integration
	Descriptive	Awareness campaigns highlight air pollution sources and health/environmental risks. Most employees have limited access to emissions data or tools.	Air emissions data is manually recorded or collected after the fact. Analysis is retrospective and used primarily for compliance reporting rather than operational control.	Static air pollutant emissions targets exist, but they are not connected to digital systems. Monitoring and control are manual and retrospective.
	Diagnostic	Targeted employees receive training on diagnostic tools to trace the root causes of air pollutant emissions. Monitoring is reactive but increasingly systematic.	Digital tools provide real-time data on emissions and trace deviations or spikes to specific processes, equipment, or operating conditions.	Policies require digital diagnostics and audits to monitor air emissions events, with systems identifying sources and patterns of emissions.

ESRS impact	Maturity level	People	Process	Policy
	Predictive	Trained employees respond to predictive alerts and forecasts warning of potential emissions spikes. Actions are taken in advance to avoid exceedances.	Predictive analytics forecast potential emissions events (e.g., venting, VOC exceedances) based on process conditions, feedstock variability, or equipment status, allowing teams to proactively prepare or intervene.	Predictive emissions modeling is embedded in operational planning and reporting, allowing early identification of potential exceedances and risk areas.
	Prescriptive	Employees collaborate with prescriptive digital systems that recommend real-time operational adjustments to reduce emissions. Confirmations and feedback are logged in production systems.	Systems automatically adjust process parameters or activate abatement measures (e.g., scrubbers, thermal oxidizers) to prevent emissions from exceeding regulatory or internal thresholds, optimizing both process and environmental performance.	Prescriptive digital control systems are mandated for high-risk processes (e.g., painting, sterilization), optimizing emissions in real time based on process data.
	Adaptive	Peer-learning platforms support ongoing knowledge exchange. Employees co-develop solutions with adaptive systems, embedding emissions minimization practices across operations.	AI-driven systems continuously monitor and optimize both core processes and emissions control systems in real time, autonomously managing emissions to stay within compliance limits and minimize environmental impact, without human intervention.	Policies require adaptive, autonomous emissions reduction systems as standard, with digital platforms self-adjusting to minimise emissions and human involvement limited to exception handling.
E2-5		Digital hazardous chemical use competency	Digital hazardous chemical use intelligence	Digital hazardous chemical use policy integration
	Descriptive	Employees are made aware of the risks and legal obligations related to hazardous chemical use. Digital tracking is limited or non-existent at the operator level.	Hazardous chemical use is logged manually or tracked on a batch-by-batch basis. Data is used for compliance or inventory purposes, with limited insight into operational efficiency or risk.	Basic substitution targets exist, but they are not linked to digital systems. Monitoring and management of hazardous substances are manual and fragmented.
	Diagnostic	Operators receive training on using digital dashboards to monitor and trace hazardous substance usage in real time.	Digital systems (e.g., ERP, MES) track hazardous material use in real time across processes, enabling better visibility, traceability, and incident response.	Policies require digital diagnostics to track hazardous substance use and identify high-risk materials and processes.
	Predictive	Employees use predictive alerts and system notifications to identify potential overuse, exposure risks, or compliance issues before they occur.	Predictive models forecast future hazardous chemical demand based on production schedules and historical usage, while also identifying risks of overuse, waste, or non-compliance.	Predictive modeling is required in procurement and process planning to anticipate hazardous chemical use and evaluate safer alternatives.
	Prescriptive	Staff work with prescriptive tools that recommend safer handling procedures or viable substitutions for hazardous chemicals, which are integrated into workflows.	Systems recommend improvements such as safer material substitutions, optimized process parameters, or smarter procurement strategies to reduce hazardous chemical use while maintaining performance.	Prescriptive substitution and phase-out systems are integrated into operational procedures, guiding real-time decision-making to reduce hazardous chemical usage.
	Adaptive	Employees contribute to digital communities of practice focused on continuous improvement and substitution strategies. Feedback loops help evolve adaptive systems that minimize hazardous chemical use.	AI systems autonomously manage procurement, process recipes, and production parameters in real time to minimize the use of hazardous chemicals, balancing cost, safety, and environmental goals without human input.	Adaptive systems are mandated to autonomously optimise and substitute hazardous chemicals, continuously learning from operations, with minimal human intervention.

ESRS impact	Maturity level	People	Process	Policy
E5-4		Digital material and resource efficiency competency	Digital total resource consumption intelligence	Digital resource use policy integration
	Descriptive	Awareness campaigns inform employees about resource consumption risks and material efficiency principles. Digital engagement is minimal.	Raw material consumption is recorded manually or after the production process. Data is used primarily for inventory or compliance, with minimal insight into efficiency.	General material efficiency targets exist, but they are not connected to digital systems. Monitoring and action are manual and disconnected from operations.
	Diagnostic	Targeted training enables staff to use digital dashboards (e.g., MES, ERP) to identify instances of material overuse and inefficiency.	Manufacturing Execution Systems (MES) and process tools provide real-time diagnostics and trends on material usage, helping identify inefficiencies and overuse as they occur.	Policies require digital diagnostics to identify material overuse and waste, using systems such as MES (Manufacturing Execution Systems) and SPC (Statistical Process Control).
	Predictive	Employees interpret predictive models that forecast material consumption risks. Preventive actions are taken to reduce waste and inefficiency.	Predictive models use production plans, product mix, and historical data to forecast material consumption, supporting proactive inventory and process optimization.	Predictive modeling of material efficiency is embedded in production planning and reporting, supporting proactive adjustments based on expected consumption and waste patterns.
	Prescriptive	Staff collaborate with prescriptive tools that recommend process or schedule adjustments to improve material efficiency. Actions are regularly implemented and reviewed.	Systems recommend adjustments to production sequences, batch sizes, or process steps to reduce material use while maintaining quality and throughput.	Prescriptive systems are embedded in daily operations, automatically adjusting processes and material inputs in real time to meet efficiency targets.
	Adaptive	Employees actively participate in knowledge-sharing platforms. Real-world insights feed into adaptive digital systems, driving ongoing improvements in resource consumption.	AI-driven systems autonomously manage material inputs and process parameters in real time, continuously optimizing for minimal raw material use without human intervention.	Policies mandate adaptive, autonomous material optimization systems, which continuously refine material use without manual input, with human oversight reserved for validation and exception handling.
E5-5		Digital waste management competency	Digital waste management intelligence	Digital waste management policy integration
	Descriptive	Awareness campaigns inform employees about waste types, segregation, and management principles. Digital tools are not actively used.	Waste data is collected manually, typically for compliance or reporting. Limited granularity and no real-time visibility into waste generation trends or causes.	Basic waste reduction targets exist, but they are not connected to digital systems. Monitoring and management are manual, with limited operational alignment.
	Diagnostic	Employees are trained to use digital dashboards (e.g., MES, SPC) to monitor waste streams and identify high-waste areas or processes.	Digital dashboards (e.g., MES, ERP) track waste generation by type (hazardous, non-hazardous) and stream (e.g., solid, liquid, packaging) in real time, enabling better categorization and basic analysis.	Policies require diagnostics of waste generation via digital tools, enabling visibility into waste types, volumes, and sources across production processes.
	Predictive	Staff use predictive dashboards to detect trends in waste generation and take early action to prevent excess waste.	Predictive models forecast potential waste generation based on production schedules, process variability, and historical trends. Risks of overgeneration or disposal bottlenecks can be anticipated.	Predictive models are required in production and waste management planning, using data trends to forecast waste generation and support proactive reduction strategies.

ESRS impact	Maturity level	People	Process	Policy
	Prescriptive	Employees engage with prescriptive systems that recommend targeted segregation strategies and process improvements to reduce waste.	Systems recommend targeted process changes, improved material sorting, recycling strategies, or scheduling tweaks to minimize waste output and enhance diversion.	Prescriptive systems are mandated to support live segregation decision-making, guiding real-time waste handling and separation to optimise recycling and disposal.
	Adaptive	Employees participate in adaptive digital platforms to share insights and co-develop strategies for continuous waste reduction, supporting zero-waste goals.	AI-driven systems continuously and autonomously optimize waste flows, recycling operations, and production processes to reduce waste generation in real time, minimizing environmental impact and disposal costs without manual intervention.	Policies require adaptive systems that manage waste automatically, using autonomous controls to reduce, segregate, and direct waste streams, with human intervention only for exceptions.
S1-9		Digital diversity & inclusion competency	Digital inclusion intelligence via accessible digital tools	Digital tools supporting diversity and inclusion policy integration
	Descriptive	Awareness campaigns introduce digital tool accessibility features (visual, audio, tactile) and their potential benefits. Usage is minimal and not yet integrated into daily tasks.	Digital tools are used only for basic onboarding or training content. Accessibility features are minimal or generic, offering limited support for diverse abilities.	General inclusion policies exist, but they have no integration with digital systems or tools. Efforts are manual and lack operational alignment.
	Diagnostic	Targeted training is provided to employees with diverse needs on how to use digital tools such as fault guides and instructional overlays adapted to specific disabilities.	Digital tools provide accessible visual, audio, or tactile overlays for specific diagnostic or instructional tasks. Support is available for selected disabilities (e.g., hearing, vision, mobility) but not yet integrated across all operations.	Policies require diagnostics of task inclusiveness and digital tool accessibility features, using digital tools to assess whether workflows and interfaces support diverse needs.
	Predictive	Employees with diverse needs use digital tool simulations to safely rehearse complex or high-risk tasks in virtual environments, building confidence and competence.	Digital tools allow employees to rehearse complex operations, supporting diverse learning styles and expanding inclusive participation in process improvement and optimization activities.	Policies require predictive reviews of workplace accessibility gaps, leveraging digital tools to anticipate and plan for inclusion challenges across roles and environments.
	Prescriptive	Employees collaborate with prescriptive AR tools providing tailored, guided instructions (e.g., voice, gaze navigation)	Prescriptive AR overlays guide real-time tasks with user-adaptive prompts, navigation, and voice commands	Policies enforce prescriptive AR tools deployment across operations to support inclusion and accessibility
	Adaptive	Employees collaborate with prescriptive digital tools that deliver tailored, real-time instructions using accessibility features (e.g., voice guidance, gaze-based navigation, haptic feedback).	Digital tools guide employees through real-time operational tasks using user-adaptive prompts, voice control, gesture recognition, and navigation; tailored to individual needs and work contexts.	Policies enforce prescriptive digital tools deployment, integrating inclusion and accessibility features directly into operational workflows to guide equitable task execution.
S1-13		Digital training & skills competency	Digital skills development intelligence	Digital tools supporting training & skills policy integration
	Descriptive	Awareness campaigns introduce digital learning tools, but engagement is limited and informal.	Human-Machine Interfaces (HMI) and dashboards are used for static data display only. They provide limited or no support for learning or skill development during task execution.	General training policies exist, but they are not linked to digital tools. Learning programs are static and not tailored to individual or operational needs.

ESRS impact	Maturity level	People	Process	Policy
	Diagnostic	Employees receive targeted training on how to use digital dashboards platforms for job-specific learning and real-time performance support.	Digital trend logs and analytics are used to identify operator errors and uncover training gaps, informing reactive training interventions or procedural updates.	Policies require diagnostics of training gaps using digital platforms, identifying current competency levels and areas needing improvement across roles.
	Predictive	Staff interpret predictive alerts indicating skill gaps or upcoming training needs, and independently engage with simulations or tailored learning content.	Predictive AR/HMI systems analyze upcoming tasks and operator profiles to forecast where task complexity or variation may require additional training, enabling proactive preparation.	Policies require predictive modeling of workforce skills gaps, using data to forecast future learning needs and align training with evolving job requirements.
	Prescriptive	Employees collaborate with prescriptive digital training tools that recommend content, pathways, or skill-building activities based on role, performance, and development goals. Feedback loops refine the learning experience.	Digital overlays and contextual guidance systems (via AR or enhanced HMI) are deployed in real time, supporting hands-on learning through adaptive instructions, alerts, and reinforcement at the point of use.	Policies mandate prescriptive training tools, delivering real-time, role-specific learning based on operational context and individual performance.
	Adaptive	Employees participate in peer-learning communities supported by digital systems that dynamically personalise training journeys. The platform evolves through employee feedback, usage data, and operational needs.	AI-driven AR bots and HMI systems autonomously personalise interfaces, learning modules, and feedback based on worker performance, learning styles, and needs, ensuring inclusive, just-in-time skill development across all roles and shifts.	Policies require adaptive digital learning platforms, which autonomously deliver personalised and inclusive training pathways, continuously optimising content with minimal human intervention.
S1-14		Digital occupational health & safety competency	Digital occupational health & safety intelligence	Digital occupational health & safety policy integration
	Descriptive	Awareness sessions introduce employees to common safety risks and the potential of basic digital tools (e.g., SPC, AR) to support safer work practices.	Basic SPC (Statistical Process Control) dashboards display process data such as temperature, pressure, or output rates, but provide limited insight into safety-specific conditions or risks.	General OHS policies exist, but they are not linked to digital systems. Safety management relies on manual procedures and reactive reporting.
	Diagnostic	Employees receive training on using diagnostic dashboards and AR overlays that highlight hazards and provide real-time safety guidance to prevent incidents.	Digital systems analyze causes of unsafe patterns, such as excessive vibrations, worker overload, or entry into restricted zones. Safety responses are reactive and reliant on manual intervention.	Policies require diagnostics of safety incidents and risks using digital tools, enabling visibility into unsafe conditions, near misses, and compliance gaps.
	Predictive	Staff interpret predictive safety alerts (e.g., fatigue risk, equipment hazards) and proactively adapt work routines or schedules to reduce risk.	Predictive tools identify early warning signs of process drift, ergonomic stress, mental/physical overload, or environmental hazards. Risk alerts are generated to guide preemptive actions.	Policies mandate predictive systems for OHS risk forecasting, including models to anticipate incidents, monitor fatigue, and identify emerging hazards.
	Prescriptive	Employees work with prescriptive systems that recommend adjustments to workflows, task sequencing, or safety procedures based on real-time risk assessments and operational data.	Systems automatically adjust task sequencing, pacing, or guidance in real time to prevent unsafe conditions. E.g., reducing manual workload, rerouting foot traffic, or triggering rest cycles.	Policies enforce prescriptive systems that dynamically adjust task flows, safety zones, and work routines in real time to mitigate identified risks.

ESRS impact	Maturity level	People	Process	Policy
	Adaptive	Employees actively contribute to digital safety platforms that learn from feedback, incidents, and near-misses. Systems continuously optimise alerts, guidance, and task flows to enhance safety performance across the organization.	AI-driven systems continuously and autonomously manage workloads, task distribution, and hazard avoidance across operations; dynamically minimizing risk exposure without the need for operator input.	Policies require adaptive safety systems embedded into all operations, with autonomous platforms continuously optimising workplace safety conditions and requiring human oversight only for exceptions.
S1-15		Digital work-life balance competency	Digital work-life balance intelligence	Digital work-life balance policy integration
	Descriptive	Basic remote collaboration tools are available (e.g., video conferencing, shared documents) but are inconsistently used. Flexible work options are informal and not digitally managed.	Tasks and workloads are tracked manually through MES reports or spreadsheets. There is limited insight into workload distribution or opportunities for remote/flexible task support.	General work-life balance policies exist, but they are not connected to digital systems. Monitoring of workload and well-being is manual and ad hoc.
	Diagnostic	Teams use digital dashboards to identify inefficiencies in remote work models, such as uneven task distribution or excessive meeting loads, and begin optimizing team workflows.	Dashboards and reports are used to analyze workload imbalances, identify signs of overwork, and assess on-site task concentration. Interventions are reactive and typically manager-driven.	Policies require diagnostics of overwork and work-life balance risks, using digital tools to track working hours, task loads, and well-being indicators.
	Predictive	Teams apply predictive simulations and Digital Twin models to forecast workload peaks, reduce unnecessary on-site presence, and support more balanced task allocation across locations.	Digital tools forecast workload peaks, identify recurring overwork patterns, and anticipate needs for on-site presence; supporting proactive workforce planning.	Policies require predictive modeling of workload and site visit risks, enabling proactive planning to mitigate burnout and support individual well-being.
	Prescriptive	Teams work with prescriptive digital systems to implement flexible schedules, redistribute tasks, and formalize hybrid work models based on team capacity and preferences.	Systems recommend or enable task redistribution, paced scheduling, and remote execution options (e.g., remote inspections, digital collaboration) to support individual and team work-life balance.	Policies mandate prescriptive systems to dynamically adjust work schedules, remote work options, and task balancing in response to real-time conditions.
	Adaptive	Adaptive digital platforms automatically optimize collaboration and workload planning using real-time data on employee stress, availability, and well-being, creating a dynamic system that supports sustainable work-life balance.	AI-enabled systems autonomously balance workloads, adjust shift schedules, and manage remote work flows in real time; optimizing productivity while protecting personal time, recovery, and flexibility across roles and sites.	Policies require adaptive digital systems that autonomously manage workload distribution, remote work scheduling, and task flows, with minimal human intervention and exception-based oversight.
G1-1		Digital ethical behavior & culture competency	Digital ethical behavior and culture intelligence	Digital ethical behavior and culture policy integration
	Descriptive	Awareness sessions introduce employees to ethical reporting channels via MES, HMI dashboards, or other digital systems. Participation is minimal and mostly reactive.	Basic MES or HMI interfaces provide manual input channels for incident or ethics-related reporting. Reporting is often underused, with limited visibility or follow-up.	General ethics reporting policies exist, but they are not linked to digital systems. Reporting is manual, reactive, and often lacks visibility or follow-up.
	Diagnostic	Targeted training on identifying misconduct or unsafe behaviors and logging them via digital tools	Systems log reported events and visualize trends, enabling diagnostic analysis of root causes and recurrence patterns related to misconduct, safety breaches, or ethical lapses.	Policies require all incident data to be logged and visualized through digital platforms such as MES (Manufacturing Execution Systems) and HMI (Human-Machine Interface) dashboards to ensure transparency and accountability.

ESRS impact	Maturity level	People	Process	Policy
	Predictive	Staff are able to interpret predictive system alerts that flag recurring ethical or safety risks. They participate in resolution efforts, such as ethics committees or improvement teams.	Predictive analytics identify hotspots for potential ethical risks based on behavioral trends, absenteeism, prior incidents, and environmental or task-related factors.	Policies mandate predictive analytics on ethics trends, enabling pre-emptive interventions by identifying patterns in behaviour, reporting frequency, and risk areas.
	Prescriptive	Employees collaborate with prescriptive digital tools that provide structured guidance and escalation paths for ethical decision-making and risk mitigation.	Systems recommend process changes, task redistribution, or shift pattern adjustments to reduce exposure to unsafe or unethical conditions and promote positive workplace culture.	Policies enforce prescriptive digital decision-support systems, guiding real-time escalation, response, and corrective actions based on ethical risk parameters.
	Adaptive	Employees engage in adaptive, peer-driven communities of practice focused on ethics. Supported by anonymized digital reporting platforms and AI-assisted coaching, these systems evolve to support a strong, self-sustaining ethical culture.	Autonomous systems monitor workflows in real time, detect potential unethical behavior, adjust operational flows accordingly, and trigger alerts or escalation protocols; ensuring rapid, anonymous, and protected reporting and intervention.	Policies require fully autonomous digital systems to manage and escalate ethical risks, maintaining anonymity, enabling continuous monitoring, and supporting a proactive, values-driven culture with minimal human involvement.

D.6. Next steps

D.6.1. How digital manufacturing technologies affect ESRS impacts

Enterprise Resource Planning (ERP)

- **E1-5:** Running an ERP system requires significant IT infrastructure, including servers and large-scale data storage. These systems consume a substantial amount of electricity to stay operational, especially since ERP servers typically run 24/7. In the context of Dutch high-tech manufacturing, the electricity used to power this infrastructure often comes from an energy mix that still includes fossil fuels. This means that although ERP adoption may seem like a digital upgrade, it can indirectly increase demand for non-renewable energy sources. Over time, this constant power draw contributes notably to overall energy consumption (Goel et al., 2024).
- **E1-6:** While ERP software itself does not emit any direct greenhouse gases (classified as Scope 1 emissions), its use does increase electricity demand, which falls under Scope 2 emissions. Since the Dutch electricity grid is not yet fully renewable, this added power usage can raise carbon emissions. Data centers, which are essential to running ERP systems, are known for their high electricity consumption, and their environmental impact, particularly in terms of carbon footprint, is significant Goel et al. (2024).
- **E5-5:** One environmental downside of ERP systems is digital obsolescence. As ERP software evolves and data requirements grow, companies are often forced to upgrade or replace servers and end-user devices to keep up. This leads to a steady accumulation of electronic waste. Unfortunately, much of this e-waste is not fully recycled (Berg et al., 2021). In the Dutch and EU context, where circular economy principles are a major policy focus, this is a concern. The continual turnover of hardware due to ERP system requirements contradicts efforts to reduce waste and retain valuable materials within the economy. It also increases the risk of pollutants being released when devices are discarded improperly.
- **S1-9:** ERP implementation can unintentionally widen social inequalities within the workplace. The high-tech manufacturing sector in the Netherlands already faces a gender imbalance, and many of the roles needed for ERP deployment, such as IT specialists, data analysts, and systems integrators, are male-dominated. If companies don't take proactive steps to include and train under-represented groups, these projects may primarily benefit workers who already have strong digital skills. This risks sidelining employees with less experience in technology. Age is also an important factor: adapting to complex ERP systems can be especially challenging for older employees. For instance, only 28% of Dutch individuals aged 65–74 possess above-basic digital skills, com-

pared to 64% among those aged 25–44 (Statistics Netherlands (CBS), 2022). Without inclusive strategies such as intuitive user interfaces, multilingual options, and varied training formats that suit different learning styles, ERP adoption may leave some employees behind and reduce workplace inclusivity.

- **S1-14:** Although ERP systems do not pose the same physical hazards as industrial machinery, they can still impact employee well-being in other ways. Psychosocial issues may arise if ERP systems enable constant data visibility or performance tracking, creating pressure on employees to meet metrics or KPIs. Dieste et al. (2022) highlights that such environments, characteristic of Industry 4.0, can lead to stress and mental health challenges. Additionally, the heavy computer use that ERP systems require can result in physical strain, such as eyestrain or repetitive stress injuries, especially if workstations are not ergonomically designed. While these concerns are not unique to ERP systems, they are still relevant considerations when implementing large-scale digital solutions in the workplace.
- **S1-15:** ERP systems can also affect employees' work-life balance. Because they provide real-time access to data and operations, both managers and staff may feel the need to stay connected after regular work hours. This could mean responding to alerts, entering data late in the evening, or joining meetings with global teams across time zones. Such demands can gradually erode personal time and increase overall working hours. Dieste et al. (2022) notes that digital systems like ERP can contribute to a "stay connected" culture, which blurs the boundary between professional and private life. If not carefully managed, this always-on environment can lead to burnout or chronic overwork.
- **G1-1:** Finally, ERP systems raise important questions about employee privacy. These systems track a vast amount of data, including detailed logs of user activity. If used ethically, this data can improve efficiency and transparency. But if misused, it can feel like surveillance and reduce employees' sense of autonomy. Experts on Industry 4.0 have cautioned that advanced digital systems can be used to micromanage or unfairly monitor workers, creating an atmosphere of mistrust. For example, using ERP data to track every small deviation or mistake could discourage initiative and support a culture of fear rather than collaboration (Dieste et al., 2022).

Advanced Planning and Scheduling (APS)

- **E1-5:** APS software uses complex algorithms, often involving artificial intelligence or large-scale optimization models, to create detailed production schedules. As digital maturity increases, these algorithms become more sophisticated and computationally demanding. Running these calculations, especially when they involve many interconnected devices and large databases, puts pressure on IT systems. The process generates significant data volumes, which can overwhelm existing infrastructure. As a result, energy use increases due to the need for constant processing power and server activity (Dieste et al., 2022).
- **E1-6:** While APS software does not directly produce greenhouse gas emissions, its energy consumption can indirectly contribute to carbon emissions through Scope 2 emissions, those linked to the electricity it uses. Running APS tools on servers around the clock or performing heavy-duty calculations, such as simulating complex factory operations, requires a substantial amount of power. If this electricity is not sourced from renewable energy, the resulting GHG emissions can be significant (Yañez-Barnuevo, 2025).
- **E5-5:** The adoption of APS in manufacturing often leads to the phase-out of older planning systems and supporting hardware. As companies seek to optimize performance, they are also more likely to upgrade their IT infrastructure regularly to support faster processing and newer software updates. This constant cycle of updates shortens the lifespan of devices and contributes to growing amounts of electronic waste. In some cases, this includes hazardous materials, depending on the type of hardware being replaced. Over time, these upgrades, while necessary for maintaining digital competitiveness, create environmental challenges related to material waste and disposal (Dieste et al., 2022).
- **S1-9:** APS technology itself is neutral, but its implementation can unintentionally affect workforce inclusion. Because these systems often require specialized skills in data analysis and digital tools, employees with advanced training are more likely to be involved in APS-driven decision-making. In contrast, workers with limited digital literacy, especially older or more traditional employees, might be left out. In Dutch high-tech companies with an aging workforce, this shift can lead to

veteran planners or operators feeling sidelined as algorithmic planning becomes central. While APS doesn't automatically change workplace diversity, it can reduce inclusion if companies don't actively support all employees through training and participation (Kohlgrüber et al., 2021).

- **S1-14:** APS systems mainly affect office-based roles like planners and managers, so direct physical hazards are minimal. However, the psychological and ergonomic impacts can be considerable. Planners may face intense pressure to meet the highly optimized schedules generated by APS tools. The need to react quickly to real-time data or unexpected disruptions can raise stress levels. On the production floor, workers might feel strained by tighter deadlines, which could lead to rushing or unsafe practices. Extended computer use also poses ergonomic risks, such as eye-strain or repetitive stress injuries, particularly if proper workstation setups are not in place. The main occupational health concern linked to APS is therefore mental strain and high cognitive demands rather than physical dangers (Kohlgrüber et al., 2021).
- **S1-15:** Because APS systems allow for constant and flexible scheduling, they can unintentionally disrupt work-life balance. Schedulers and planners may feel the need to monitor or adjust production plans outside regular working hours, especially when APS tools run simulations overnight or when last-minute changes are frequent. The system's "always-on" capability means employees can log in at any time, which might seem efficient but can easily lead to overwork or burnout if boundaries aren't enforced. This persistent connectivity can slowly erode personal time and create long-term well-being concerns (Kohlgrüber et al., 2021).
- **G1-1:** While APS is designed to optimize operations, its use can sometimes conflict with ethical principles like fairness and transparency. For example, an algorithm might consistently assign less favorable shifts, such as night shifts, to certain employees if that results in higher overall efficiency. If managers rely too heavily on these algorithmic decisions without human oversight, it can undermine workplace morale. Workers may feel that they have little ability to question or challenge decisions made "by the system," leading to a sense of disempowerment and reduced trust in management (Bakshi and Paulson, 2022).

Manufacturing Execution System (MES)

- **E1-5:** MES software is designed to run continuously on production floors, connecting with machines, sensors, and data capture devices. This always-on setup, which includes industrial PCs, terminals, and servers, adds to the factory's overall energy consumption. As these systems collect real-time data from IoT devices across the floor, the demand on computing resources grows. Processing and storing all this information requires more power, especially when cloud services or extensive networking are involved. If the energy used is not fully renewable, the environmental footprint becomes more pronounced. MES systems, by nature, contribute to energy use both through local IT equipment and the broader digital infrastructure they depend on (Dieste et al., 2022).
- **E1-6:** Although MES software doesn't emit greenhouse gases directly on-site (Scope 1), it does lead to indirect emissions through the electricity it consumes (Scope 2). An interesting paradox arises when MES increases production efficiency. If output rises but energy efficiency per unit does not improve, the overall energy demand can still grow. For example, if a factory runs longer shifts or operates machines at higher capacity due to more effective scheduling or throughput gains, total energy-related emissions may actually increase (Bakshi and Paulson, 2022).
- **E2-4:** MES implementation also leads to more equipment running continuously. Devices such as sensors, monitors, and wireless access points stay active, contributing to steady energy consumption. This extra power draw can trigger secondary systems, like HVAC units or backup generators, to operate more frequently. Though these sources may seem minor, they can emit pollutants such as diesel exhaust or ozone from electronics. Over time, these indirect emissions become part of the system's broader environmental impact (Toczé et al., 2022).
- **E5-5:** Like many digital systems, MES hardware eventually becomes obsolete. As new technologies emerge, companies often upgrade MES terminals or replace older sensors with more advanced models. Devices that no longer meet performance needs are decommissioned, creating electronic waste. Unfortunately, as seen in many Industry 4.0 case studies, a large portion of this outdated equipment is discarded without proper recycling. This trend not only contributes to the growing e-waste problem but also undermines sustainability goals by allowing valuable materials to go unrecovered (Dieste et al., 2022).

- **S1-9:** Introducing MES can change how work is performed on the shop floor. Tasks that were once done manually, like logging production times or recording defects, can be automated or digitized. While this improves efficiency, it can also reduce or redefine certain low-skill roles. Employees who previously handled these tasks, often older or less formally trained, may find themselves at a disadvantage unless companies provide effective retraining. If not addressed, these changes could reduce workplace inclusion and increase the risk of job displacement for vulnerable groups (Dieste et al., 2022).
- **S1-14:** MES systems bring humans into closer interaction with machines and data in real time, which can create new occupational health risks. One concern is information overload. Operators may receive constant alerts or status updates, leading to stress, distraction, or even alarm fatigue. When attention is divided, the risk of human error increases. Additionally, heavy reliance on screen-based instructions can reduce workers' situational awareness, which is important for safety in dynamic factory environments. While not physically hazardous on their own, MES terminals introduce ergonomic and eyesight issues due to increased screen time, especially compared to more traditional, manual tasks (Dieste et al., 2022)..
- **S1-15:** Because MES platforms operate around the clock, they can blur the boundaries between work and personal time for some staff. For example, if a system issue arises after hours or if urgent production data needs review, engineers or IT personnel may be contacted during their time off. MES also increases the pace of information, real-time dashboards allow managers to monitor production progress at any time. This constant visibility can create pressure for immediate responses, even outside standard work hours, gradually affecting work-life balance (Dieste et al., 2022).
- **G1-1:** MES gives companies detailed insight into both machine performance and individual worker productivity. While this visibility can improve operations, it also introduces risks around employee surveillance. If performance metrics are used to monitor workers too closely, tracking their speed, accuracy, or errors, it may create a culture of mistrust. Employees might feel they are constantly watched or evaluated, which can lower morale and engagement. Experts have raised concerns that such digital monitoring, if unchecked, could lead to exploitative practices or misuse of personal data (Dieste et al., 2022).

Supervisory Control and Data Acquisition (SCADA)

- **E1-5:** SCADA systems rely on a network of sensors, programmable controllers (PLCs or RTUs), and centralized workstations that operate continuously to monitor and control industrial processes. While each individual device may consume little power, the total energy use across an entire facility can be substantial. Thousands of data points may be updated every second, which places a high load on servers and networking equipment. This constant demand increases energy consumption for data processing and communication. Furthermore, because SCADA requires high reliability, backup power systems like uninterruptible power supplies (UPS) are often used, adding redundancy and associated energy inefficiencies (Dieste et al., 2022; Berg et al., 2021).
- **E1-6:** SCADA systems typically manage physical processes but do not produce emissions themselves (Scope 1). However, the electricity needed to power the SCADA infrastructure, including servers, controllers, and operator workstations, contributes to indirect emissions (Scope 2), especially if the power source is not renewable (Bakshi and Paulson, 2022).
- **E5-5:** Over time, SCADA components such as sensors and controllers become outdated or fail, necessitating upgrades. When facilities modernize their SCADA systems, such as replacing older PLCs with newer models, large volumes of electronic waste can be generated. This is particularly true during full-scale retrofits, where hundreds of devices might be decommissioned simultaneously. Newer SCADA systems may also use wireless sensors powered by batteries, which must be disposed of when depleted. Industry practitioners have raised concerns about the growing amount of waste electrical and electronic equipment (WEEE) resulting from rapid digitalization (Dieste et al., 2022).
- **S1-14:** One of the key occupational safety concerns with SCADA is the risk of system failure. If incorrect data is processed or transmitted, the system might issue flawed commands that lead to equipment malfunction or unsafe conditions. In severe cases, this could result in damage or even explosions. Additionally, if operators become overly reliant on SCADA and neglect physical inspections, early warning signs might be missed until alarms are triggered, potentially reducing

response time. Maintenance tasks also carry risk: if automated machinery is not properly shut down during repairs, it may activate unexpectedly, posing a danger to workers (Kohlgrüber et al., 2021).

- **S1-15:** Because SCADA systems operate 24/7, they often require continuous monitoring, either through shift rotations or on-call responsibilities. This can negatively impact the work-life balance of engineers and technical staff. For example, SCADA alarms may notify personnel at any time of day or night about critical issues, requiring immediate attention. As Coldwell (2019) observed, digital systems can blur boundaries between work and personal time, encouraging a culture where employees are expected to stay connected even when off duty.
- **G1-1:** SCADA offers granular visibility into system performance and operator actions. While this can improve accountability and operational control, it also raises ethical concerns about worker privacy. Employees may feel constantly monitored, which could reduce trust and morale. If used inappropriately, such systems might contribute to a surveillance-like environment. Researchers have highlighted risks such as exploitative oversight and unclear boundaries around data use, especially in environments where transparency and consent are not clearly established (Dieste et al., 2022).

Programmable Logic Controllers (PLCs)

- **E1-5:** While individual PLCs consume very little electricity, the combined energy use of thousands of units operating around the clock across a factory can become significant. Most energy in manufacturing is used by large equipment such as motors and compressors, but control systems like PLCs also contribute to the overall load. When these ancillary devices are not offset by renewable energy sources or high-efficiency system designs, they slightly reduce the overall energy efficiency of industrial operations. Over time, the cumulative electricity consumption of a large PLC network adds to a plant's energy footprint (Nederman, 2025).
- **E1-6:** The electricity used to operate PLCs contributes indirectly to greenhouse gas emissions through Scope 2 emissions. This impact depends on the energy mix powering the facility. In 2022, only about 40% of electricity in the Netherlands came from renewable sources. The majority, approximately 54%, was generated from fossil fuels like natural gas and coal. As a result, running PLC systems under such conditions indirectly leads to GHG emissions (International Trade Administration, 2025).
- **E5-5:** When PLC units reach the end of their lifecycle, they contribute to the growing global stream of electronic waste. Without proper circular economy practices, these devices are often discarded instead of recycled. In the Netherlands, approximately 366 kilotons of electronic waste were produced in 2018, but only about half was recycled in line with established standards. The rest was either exported, often to regions with lower environmental safeguards, or processed informally through scrap channels, increasing the risk of improper handling and material loss (Brink et al., 2021).
- **S1-9:** The field of automation and control engineering, which includes work on PLC systems, is marked by underrepresentation of women and other minority groups. This lack of diversity can limit the inclusion of different perspectives and perpetuate an unequal workplace culture. If companies do not actively promote inclusion and equity, increasing reliance on PLC-based automation could worsen existing gender and diversity gaps in high-tech manufacturing environments (Ravichandran, 2023).
- **S1-14:** PLC-based automation can reduce physical risks on the factory floor by minimizing the need for human interaction with hazardous machinery. However, it can introduce new challenges related to psychosocial well-being and ergonomics. As automation increases, employees may experience reduced autonomy or a sense of disconnection from their tasks. Research from the EU suggests that highly standardized, digitally managed work can feel fragmented and lead to job dissatisfaction. Additionally, monitoring equipment through PLC interfaces or human-machine interfaces (HMIs) over extended periods may cause physical strain, such as eyestrain or musculoskeletal discomfort, particularly if ergonomic workstation design is lacking (Vázquez et al., 2024).
- **S1-15:** Digital automation systems like PLCs enable continuous monitoring and remote oversight, which can blur the distinction between working hours and personal time. Engineers and support staff may be expected to respond to machine alerts or production issues outside of normal work-

ing hours. This always-connected environment can make it difficult to disconnect, posing a risk to work-life balance and increasing the potential for burnout (Dieste et al., 2022).

Human-Machine Interfaces (HMIs)

- **E1-5:** HMIs are commonly deployed across factory floors for real-time process monitoring and control, and many of these units operate 24/7. Although the energy consumption of a single HMI is relatively modest, their continuous operation contributes to the facility's base load electricity demand. When multiple HMIs are in use, and especially if they include older models or high-brightness displays, the energy impact grows. Older units can be particularly inefficient and may generate heat that increases the need for air conditioning in control rooms. In facilities not powered entirely by renewable energy, this continuous draw contributes to fossil fuel-based electricity consumption, undermining broader energy-efficiency goals (Toczé et al., 2022).
- **E1-6:** The operation of HMIs results in Scope 2 emissions because of the electricity required to power them. In the Netherlands, a significant portion of the grid mix still comes from fossil fuels, such as natural gas and coal. As a result, keeping HMIs running around the clock contributes indirectly to greenhouse gas emissions from electricity generation (International Trade Administration, 2025).
- **S1-9:** HMI design and industrial IT reflect the broader diversity gaps present in the tech and engineering sectors. Women and minority representation in industrial software development, UI/UX design, and ergonomics remains low. In the Netherlands, women make up fewer than 20% of technical roles. This lack of diversity can affect product inclusiveness. For instance, if HMIs are designed primarily by a homogeneous group, such as young male engineers, they may not adequately accommodate the needs of older workers, women, or users with different cognitive styles. As a result, usability issues may arise, and opportunities for more inclusive participation in digital transformation efforts may be missed (Ravichandran, 2023; Eurostat, 2025).
- **S1-14:** The shift toward screen-based operations brings new occupational health and safety challenges. Operators may spend extended periods sitting or standing at HMI stations, which can lead to musculoskeletal problems, especially if the workstations are not ergonomically designed. Poor positioning, such as screens placed too high or low, or improper lighting causing glare, can result in neck and eye strain. Psychologically, workers may experience vigilance fatigue from constant screen monitoring or stress caused by frequent system alerts. Alarm overload is a particular concern, as repeated notifications can create pressure and reduce focus over time (Vázquez et al., 2024).
- **G1-1:** HMIs often log user interactions, including alarm acknowledgments and data entry times. While this can improve accountability and traceability, it also raises ethical concerns around worker privacy. Management might use this logged data to track individual performance metrics, such as how quickly a worker responds to a system alert. If not handled transparently and fairly, such monitoring can feel intrusive and may lead to reduced trust or morale (Riso and Litardi, 2024).

Distributed Control Systems (DCS)

- **E1-5:** DCS installations involve a network of controllers, servers, operator terminals, and communication hardware distributed across a plant. These systems operate continuously, often with built-in redundancy to ensure reliability. In large facilities, a DCS may consist of dozens of controller chassis and computer terminals, all drawing power around the clock. This infrastructure adds a steady load to the plant's overall energy consumption. In addition, DCS components are often housed in climate-controlled environments, such as air-conditioned control rooms or equipment cabinets, which increases energy use for cooling (Toczé et al., 2022).
- **E1-6:** The 24/7 operation of DCS hardware contributes to Scope 2 greenhouse gas emissions via electricity consumption. In high-energy industries such as chemical production or semiconductor fabrication, DCS systems may form part of a broader power demand that reaches into the megawatt range. If this energy is sourced partly from fossil fuels, as is still the case in the Netherlands, it contributes to indirect GHG emissions. Some facilities also use diesel generators or uninterruptible power supplies (UPS) as backup systems. Periodic testing of these generators can lead to Scope 1 emissions through direct release of exhaust gases (Toczé et al., 2022).
- **E2-4:** Although DCS equipment does not emit pollutants under normal operating conditions, it is indirectly associated with emissions from backup power systems. Facilities typically rely on

diesel generators to maintain DCS functionality during power outages, and these systems must be tested regularly. These tests release pollutants such as carbon monoxide (CO), nitrogen oxides (NO_x), and particulate matter. Additionally, DCS systems include a large volume of electronic components, and improper disposal of these can result in localized pollution events, such as smelting that releases heavy metal fumes (WBPS, 2024; Brink et al., 2021).

- **E5-5:** While DCS hardware is built to last, it eventually becomes obsolete due to hardware aging or discontinued vendor support. When an entire system is replaced, several tons of specialized electronic waste may be generated at once. This presents a recycling challenge: DCS hardware is not easily repurposed due to its system-specific design, and disassembly for material recovery is labor-intensive and inefficient. Some facilities choose to store outdated DCS units indefinitely, wasting potential value, while others may dispose of the equipment improperly (Toczé et al., 2022).
- **S1-14:** Operating a DCS involves high cognitive demands and responsibility. A mistake at the interface can have serious consequences, including safety incidents or production downtime. Operators must often manage complex alarms, interpret fast-changing data, and respond quickly to avoid escalation. This level of pressure can lead to significant psychosocial stress. Alarm overload is a particular concern, as frequent or poorly prioritized alerts can increase anxiety and hinder decision-making (Vázquez et al., 2024).
- **S1-15:** DCS platforms support remote monitoring and centralized control, which often results in staff being on call beyond normal working hours. In continuous-process industries, engineers or control room personnel may be required to respond at any time to faults or system alerts. Remote connectivity, via VPNs, cloud platforms, or smartphone apps, means that DCS-related responsibilities can follow employees outside of the workplace. This persistent connectivity risks eroding work-life balance and reducing employees' ability to fully disengage from work (Dieste et al., 2022).
- **G1-1:** DCS systems typically record every operator action and system adjustment, creating detailed digital logs. While this can support accountability and traceability, it also raises ethical considerations. If these logs are used to unfairly assign blame for incidents beyond a worker's control, trust and morale may be undermined. Best practices suggest involving employees in conversations about performance monitoring and ensuring transparency around how operational data is used (Riso and Litardi, 2024).

Cloud-Based Storage

- **E1-5:** Cloud-based storage in manufacturing involves outsourcing the management of data, such as production metrics, inventory records, and supply chain information, to off-site data centers. These facilities are highly energy-intensive due to their need to run servers, cooling systems, and networking infrastructure continuously. Additionally, cloud service providers often replicate data across multiple geographic locations for redundancy and reliability. While this improves uptime and resilience, it also multiplies the energy required for both storage and cooling, thereby increasing the overall energy footprint (Toczé et al., 2022).
- **E1-6:** The greenhouse gas emissions associated with cloud storage stem from both indirect and direct sources. On the Scope 2 level, data centers draw electricity from the grid, which in the Netherlands still includes a significant proportion of fossil fuels. This means their energy use translates into GHG emissions at the power generation stage. On the Scope 1 level, most large data centers also maintain diesel backup generators to ensure uninterrupted service during outages. These generators are tested regularly and used occasionally, releasing greenhouse gases and pollutants directly into the environment (WBPS, 2024).
- **E2-4:** While data centers do not pollute during normal operations, their diesel backup systems can impact local air quality. During generator tests or emergency power events, they emit exhaust that includes nitrogen oxides (NO_x), particulate matter (soot), carbon monoxide (CO), and unburned hydrocarbons. In areas with dense concentrations of cloud infrastructure, such as the Amsterdam region, these emissions can add up. Local authorities have raised concerns about the cumulative environmental effects, and in some cases, have considered stricter permitting for generator use due to pollution risks (WBPS, 2024).
- **E5-5:** The physical hardware behind cloud services, especially servers, has a relatively short life-cycle. Components are often upgraded or replaced every 3 to 5 years to keep pace with tech-

nological demands. Without circular economy practices in place, this rapid turnover contributes to a growing volume of electronic waste. Discarded server units, storage drives, and network equipment add to the global e-waste stream, which is already among the fastest-growing waste categories (Brink et al., 2021).

- **S1-15:** Cloud platforms allow constant, remote access to digital systems, enabling employees to log in from anywhere and at any time. While this flexibility supports productivity, it can also encourage an "always online" culture. Workers may feel pressure to check production dashboards, respond to alerts, or monitor inventory data during evenings, weekends, or holidays, simply because the systems are accessible on their mobile devices. If left unmanaged, this persistent connectivity can erode personal time and lead to poor work-life balance (Dieste et al., 2022).

Industrial Internet of Things (IIoT)

- **E1-5:** Individual IIoT devices, such as temperature sensors, vibration monitors, or asset trackers, typically consume very little power. Many run on small batteries or draw just a few watts of electricity. However, when deployed at scale, the cumulative energy impact becomes substantial. In a dense IIoT environment, hundreds or even thousands of devices may be running simultaneously, transmitting data wirelessly around the clock. This constant operation requires continuous power, either directly from wired sources or indirectly through frequent battery replacements and charging, which increases the site's overall energy consumption (Parmentola et al., 2022).
- **E1-6:** The additional electricity required to support large IIoT deployments contributes to Scope 2 greenhouse gas emissions, especially when the power source is not renewable. Moreover, IIoT systems may enable or trigger the use of other energy-consuming or emission-producing equipment. For example, data collected from IIoT devices might activate battery-powered drones, automated guided vehicles (AGVs), or other automated tools. These machines themselves may contribute to direct (Scope 1) emissions depending on their power source and frequency of use (Parmentola et al., 2022).
- **E5-5:** The IIoT ecosystem is characterized by large numbers of compact, short-lifespan devices. Many sensors are not designed for long-term durability or easy maintenance, some are even intended to be disposable, such as single-use pallet trackers or low-cost temperature loggers. This leads to a rapid accumulation of electronic waste, particularly in the form of small devices. These items often escape proper collection and recycling systems. Because of their size, they are easily overlooked, discarded in general waste streams, or stockpiled in storage without formal disposal. Over time, their cumulative contribution to the waste electrical and electronic equipment (WEEE) stream is significant (Yuki, 2022).
- **S/G impacts:** IIoT devices do not independently create social or governance impacts; rather, such effects arise only in combination with broader digital systems, such as enterprise platforms, cloud services, or automated control technologies. Therefore, social and governance considerations related to IIoT are addressed under those systems rather than the devices themselves.

Edge Devices

- **E1-5:** Edge devices, including sensors, local controllers, and embedded processing units, are increasingly deployed in industrial environments to enable real-time decision-making close to the source of data. These devices often run continuously, drawing power 24/7. While each device consumes relatively little energy, their cumulative deployment across a factory or facility can substantially raise total electricity demand. If this power is not sourced from renewable energy, the increased load contributes to higher non-renewable energy consumption, which may offset any efficiency gains achieved through digitalization (Nokia, 2020).
- **E1-6:** Edge devices generally do not produce direct emissions (Scope 1), but their continuous operation leads to indirect emissions (Scope 2) via electricity use. In regions where the energy grid still relies on fossil fuels, the power needed to run these devices contributes to greenhouse gas emissions associated with industrial digital infrastructure (Toczé et al., 2022).
- **E5-5:** The growing use of edge devices adds to the electronic waste (e-waste) problem, particularly due to the small size and short lifespan of many devices. Items like sensors and smart controllers are often discarded informally, tossed into general waste or left unused in storage, especially when their individual economic value is low. Despite their small size, these devices collectively contain critical metals and hazardous materials. Their improper disposal undermines

circular economy goals and represents a missed opportunity for material recovery (Toczé et al., 2022).

- **S1-14:** Autonomous edge devices can introduce new occupational safety risks. When such devices are used to control equipment without human oversight, failures in data interpretation or logic, such as a misread sensor input, could trigger unsafe actions. For example, an edge AI component might activate or shut down machinery based on incorrect data, potentially endangering workers or damaging equipment. Ensuring safety in edge-enabled automation requires robust fail-safes and careful system validation (International Labour Organization, 2025).
- **G1-1:** Edge devices collect and process large volumes of data, some of which may relate to worker activities, production workflows, or proprietary processes. This raises important questions about data ethics and privacy. Organizations must ensure that data from edge systems is managed transparently and responsibly. Misuse, such as invasive monitoring or opaque algorithmic decisions, can damage trust and violate ethical norms. Clear data governance policies are essential to prevent surveillance and protect worker rights (Riso and Litardi, 2024).

Data Lakes, Databases, and Historians Based on internal discussions at the internship company, the environmental and social impacts of data lakes, databases, and historians largely align with those of cloud-based infrastructure, unless these systems are explicitly hosted on-premises. In most cases, these storage solutions are operated via external cloud platforms, meaning their energy consumption, greenhouse gas emissions (Scope 1 and 2), and e-waste considerations are already captured under the broader category of cloud services. Their contribution to issues such as 24/7 access and work-life balance also mirrors that of cloud-based systems, particularly as they enable remote data access, real-time monitoring, and persistent connectivity. Therefore, the sustainability considerations for these data management technologies are understood to fall under the same umbrella as those discussed in the cloud storage section.

On-Premises Industrial Connectivity

- **E1-5:** While individual networking devices, such as switches, routers, and gateways, consume only a small amount of electricity (typically a few to tens of watts), their cumulative impact can be significant. In high-tech manufacturing environments, it is common to have hundreds of such devices running 24/7. Without power management features like sleep modes or Energy Efficient Ethernet, this continuous draw contributes to a steady background load on the facility's energy consumption. Despite their relatively small individual footprint, unmanaged networking infrastructure can quietly undermine energy-efficiency efforts across a site. Only recently have manufacturers begun exploring technologies such as scheduled port power-down and optimized device provisioning to reduce this hidden energy burden (Toczé et al., 2022).
- **E1-6:** The greenhouse gas emissions associated with industrial connectivity infrastructure arise primarily from electricity use (Scope 2). This is especially relevant when the facility's electricity comes from a carbon-intensive energy mix. Furthermore, inefficient network configurations, such as maintaining redundant or parallel legacy systems, can require additional hardware and prolong the use of outdated, less efficient equipment, further increasing emissions (Toczé et al., 2022).
- **E5-5:** Network upgrades are a common part of digital modernization in manufacturing. Transitions from older technologies, such as fieldbus systems, to modern protocols like Industrial Ethernet or Time-Sensitive Networking often result in electronic waste. This includes obsolete routers, interface cards, patch panels, and cabling. A notable issue is the handling of legacy network cables: during facility renovations, these are frequently abandoned inside walls or ceilings, or sent to landfill instead of being recycled. This represents both a lost opportunity for copper recovery and a barrier to achieving circular economy goals in industrial infrastructure (European Commission, 2025c).

Digital Twin

- **E1-5:** Operating digital twins involves substantial energy use, as they depend on continuous data acquisition, real-time analytics, high-performance computing, and often cloud-based storage and processing. The supporting ICT infrastructure, including sensors, networked devices, edge servers, and cloud platforms, draws significant electricity. In scenarios where renewable energy is not used, the increased energy demand from digital twins may partially or fully offset the

efficiency gains they are intended to deliver. Companies that do not optimize energy sourcing and system design may find the sustainability benefits of digital twins limited (ZEW – Leibniz Centre for European Economic Research, 2022).

- **E1-6:** The intensive power requirements of digital twin platforms contribute to Scope 2 greenhouse gas emissions, particularly when powered by non-renewable energy sources. High computational workloads, frequent data transmissions, and persistent server activity all translate into elevated energy consumption and associated GHG emissions, unless fully offset by green electricity procurement (Spleth et al., 2024).
- **E5-5:** The adoption and continuous evolution of digital twins contribute to increasing electronic waste. To maintain an accurate and current digital representation of physical assets, companies frequently upgrade their sensors, servers, and other data-generating equipment. This rapid hardware turnover leads to more discarded electronics, much of which is not handled through circular economy practices. Components are often retired before end-of-life due to performance needs, increasing the volume of prematurely disposed devices (Bakshi and Paulson, 2022).
- **S1-14:** Digital twins can introduce occupational health and safety risks related to cognitive strain. Employees interfacing with these systems may be required to process and respond to large volumes of real-time data, which can lead to stress, fatigue, and information overload. Research on digital technologies in Industry 4.0 environments shows that while ICT tools enhance visibility and monitoring, they can also create new mental and emotional burdens on workers. These risks must be addressed through interface design, workload management, and adequate training (Obasi and Benson, 2025).
- **S1-15:** Because digital twins offer continuous insights and operate on a 24/7 basis, they can blur the boundary between work and personal time. Alerts, simulation outputs, or operational insights may arrive outside standard working hours, potentially creating pressure for staff, especially engineers and managers, to stay connected and respond at all times. This is particularly challenging in globally distributed manufacturing environments, where time zone differences exacerbate the demand for round-the-clock attention. If not properly managed, this connectivity can negatively affect work-life balance (Llave, 2025).

Advanced Process Control (APC)

- **E1-5:** Implementing Advanced Process Control (APC) systems involves installing additional sensors, control hardware, and continuously running complex algorithms. This infrastructure increases the electrical load within a facility. Empirical studies have shown that digital automation, including APC, often correlates with higher overall electricity use at the plant level. While APC aims to optimize processes, its own servers, instrumentation, and computational operations consume energy. Moreover, if APC enables increased production speeds or higher capacities, total energy use may rise, even if energy per unit of output improves. The net energy impact can be negative if efficiency gains are outweighed by the energy demands of the system itself (ZEW – Leibniz Centre for European Economic Research, 2022).
- **E1-6:** APC contributes to Scope 2 emissions via the electricity used to power advanced controllers, cloud-based analytics, and associated data infrastructure. In some cases, APC enables production increases, which may raise Scope 1 process emissions unless balanced by energy or material efficiency improvements. A McKinsey analysis emphasizes that only well-tuned, context-sensitive APC implementations consistently yield sustainability benefits. Poorly configured systems may cause instability, leading to frequent equipment start-ups or shutdowns, which are especially emission-intensive and can result in a rebound effect (Görner et al., 2020).
- **E5-5:** As APC systems are deployed and updated, older control hardware is frequently replaced. Legacy PLCs, analog instruments, and outdated sensors are often discarded, contributing to the growing stream of electronic waste. Because APC requires high-precision instrumentation, sensors are subject to frequent calibration and more rapid replacement cycles. These maintenance and upgrade demands generate a continuous flow of small, specialized e-waste that is difficult to manage through standard recycling systems (Toczé et al., 2022).
- **S1-14:** One occupational safety risk associated with APC is reduced operator engagement. When automated systems take over routine control tasks, operators may become passive observers. This can lower vigilance and delay appropriate reactions during unexpected events, a phenomenon often referred to as the “automation paradox.” If a system alert or failure occurs and the operator

is unprepared to interpret or respond due to unfamiliarity or disengagement, safety risks may increase. Additionally, complex APC systems can produce cryptic or non-intuitive messages, and if operators are not well-trained, this can slow their response to critical situations (Bakshi and Paulson, 2022).

- **S1-15:** APC systems typically run continuously and often support remote connectivity, which can extend work responsibilities beyond traditional shifts. Engineers or specialists may be expected to respond to control system alerts during nights or weekends, given that the infrastructure is capable of issuing real-time notifications. This persistent connectivity may contribute to an erosion of work-life boundaries, particularly if no clear protocols exist to manage on-call expectations (Llave, 2025).
- **G1-1:** APC has implications for workforce structure and ethical labor practices. Because it automates tasks traditionally performed manually, it may lead to job displacement. Organizations have a social responsibility to mitigate these impacts by offering affected employees retraining, reskilling, or transition support. Using APC solely as a cost-cutting tool, without regard for job impacts, risks undermining social sustainability goals (Bakshi and Paulson, 2022).

Manufacturing Control Tower

- **E1-5:** Control towers are highly data-driven digital systems that typically rely on cloud computing, IoT-enabled infrastructure, and powerful visualization platforms for real-time decision-making. Their operation involves continuous data collection, transmission, and processing from numerous devices and locations. For instance, a supply chain control tower may receive data from hundreds of sensors, update visual dashboards in real time, and perform predictive analytics using AI. This architecture consumes substantial energy across both local hardware (displays, terminals, networking devices) and remote servers. While control towers may enhance operational efficiency, they risk shifting energy demand from physical production to the digital ecosystem, potentially offsetting gains if not supported by low-carbon energy sources (Toczé et al., 2022).
- **E1-6:** The electricity required to operate a control tower's IT systems, including cloud platforms, servers, and connected devices, results in Scope 2 greenhouse gas emissions. This is especially relevant in regions with carbon-intensive grid mixes. As control towers scale up in complexity and data intensity, so too does their energy footprint and corresponding emissions (Toczé et al., 2022).
- **E5-5:** Deploying a control tower contributes to electronic waste over time. All supporting hardware, such as sensors, data collection units, computers, and display terminals, will eventually reach end of life. Given the pace of technological change, the turnover of digital equipment in such systems is often rapid. Furthermore, if a control tower is not configured with sustainability criteria, it may optimize primarily for throughput, responsiveness, or service level, inadvertently tolerating or even exacerbating material waste in the name of operational efficiency. This dual impact, hardware obsolescence and operational trade-offs, represents a sustainability concern (Brink et al., 2021).
- **S1-14:** Employees working in control tower environments, usually office-based roles, face common ergonomic and psychosocial risks. Prolonged screen time can lead to eye strain, poor posture, and sedentary health issues. Additionally, real-time monitoring duties during crises (e.g., supply disruptions or equipment failures) can induce high stress. Control tower staff often function as the "nerve center" of the operation, with responsibility for fast and high-stakes decision-making. The resulting pressure, particularly during emergencies, can negatively affect mental health. Research on digital workplaces identifies stress and cognitive overload as emerging risks, and control towers exemplify these conditions (Llave, 2025).
- **S1-15:** To support global manufacturing and supply chains, control towers frequently operate on a 24/7 basis. Employees may work in rotating shifts to maintain continuous coverage, including nights and weekends. Unlike traditional shift roles, digital functions such as planning and analytics may also become part of the shift structure, extending non-standard hours into previously daytime-only work domains. If not managed carefully, this can disrupt personal routines and exacerbate work-life balance issues for employees (Llave, 2025).
- **G1-1:** Control towers often involve granular visibility into production metrics, logistics movements, and even individual worker performance. If integrated with wearable sensors, tracking systems, or detailed logs, they can collect sensitive data, such as worker movement, task completion speed,

and real-time outputs. While this can enhance efficiency and accountability, it also raises ethical concerns around privacy and surveillance. Without proper governance, such systems risk undermining trust and autonomy in the workplace (Riso and Litardi, 2024).

Statistical Process Control (SPC)

- **E1-5:** Implementing Statistical Process Control (SPC) in manufacturing environments involves setting up sensors, data acquisition networks, and computing systems to enable real-time monitoring and analysis of process stability. While these systems enhance quality assurance and reduce variability, the associated digital infrastructure, such as industrial PCs, servers, and communication gear, adds to the facility's ongoing electricity consumption. As SPC adoption scales up, the cumulative energy demand across devices and analytics systems becomes a meaningful contributor to the site's overall energy use (Diver, 2022).
- **E1-6:** The increased electricity consumption tied to SPC systems results in higher Scope 2 greenhouse gas emissions, particularly when powered by fossil fuel-based grids. Additionally, some installations may generate Scope 1 emissions if auxiliary heating or cooling systems are required to maintain temperature stability for sensitive electronics. As manufacturing becomes more automated and computationally intensive, both direct and indirect emissions can rise unless explicitly mitigated through energy-efficient design and renewable sourcing (Liu et al., 2024a).
- **E5-5:** SPC infrastructure includes a variety of electronic components, sensors, industrial computers, and network interfaces, all of which have finite operational lifespans. As technology advances, companies often replace or upgrade these components to ensure accuracy, performance, or system compatibility. This leads to periodic waves of electronic waste. If old devices are not recovered through circular programs, they may contribute to the broader e-waste problem. Studies have also found that building smart factories, where SPC is commonly integrated, can increase short-term waste costs by approximately 7% due to discarded equipment, packaging, and retrofit debris (Liu et al., 2024a).
- **S1-14:** In SPC-driven production environments, operators must frequently respond to real-time alarms or out-of-control process signals to prevent product quality issues or unplanned downtime. This demand for constant vigilance can lead to psychological stress and mental fatigue. Furthermore, when SPC data is used not just for process monitoring but also to assess individual worker performance, it may create a perception of surveillance. This psychosocial pressure can negatively affect trust and morale. From a physical standpoint, more time spent in control rooms monitoring SPC dashboards can result in ergonomic concerns, including eye strain, sedentary behavior, and musculoskeletal discomfort (Llave, 2025).

Augmented Reality (AR)

- **E1-5:** The use of AR in high-tech manufacturing typically involves a combination of head-mounted displays, handheld tablets, and backend IT systems for serving real-time content, such as 3D models or live video feeds. AR operations require considerable computing power to render graphics, track spatial data, and integrate with IoT systems. At scale, AR deployments, such as using hundreds of AR headsets for assembly support or employee training, demand higher electricity usage for device charging and continuous wireless connectivity. Cloud-based AR platforms and real-time remote support services further contribute to energy consumption due to heavy data transmission and processing loads (AR for Enterprise Alliance (AREA), 2025).
- **E1-6:** AR systems contribute to Scope 2 greenhouse gas emissions through the electricity required to power both end-user devices and their associated backend infrastructure. The more frequently and extensively AR is used across operations, the higher the resulting energy-related emissions (AR for Enterprise Alliance (AREA), 2025).
- **E5-5:** Introducing AR into manufacturing environments presents new e-waste and circular economy challenges. AR hardware, including smart glasses and headsets, tends to become obsolete quickly due to rapid technological advancements and software compatibility issues. Companies may replace hardware frequently in pursuit of performance, resulting in more discarded devices. These devices are often not modular, hard to repair, and difficult to recycle due to the combination of electronic and optical components. Current recycling processes for AR equipment remain limited in efficiency and scale. As a result, AR adoption can accelerate the growth of electronic waste in a sector already struggling to implement effective circularity (AR for Enterprise Alliance

(AREA), 2025; Cosio et al., 2023).

- **S1-9:** AR implementation raises inclusion concerns. Not all workers can comfortably or safely use AR devices. Employees with vision impairments, neurological conditions (such as epilepsy), or physical discomfort from wearing headsets may be excluded from tasks that rely on AR. If AR becomes a standard tool for performing key operations, individuals who cannot use it may face reduced access to job opportunities. Additionally, digital skill disparities can lead to generational gaps: younger, tech-savvy workers may adapt more quickly to AR, while older employees may require more support. Without inclusive design and training, AR can inadvertently widen diversity and accessibility gaps (Cosio et al., 2023).
- **S1-14:** Although AR technologies aim to enhance safety and efficiency, they introduce new occupational health risks. Wearing AR headsets for long durations can lead to eyestrain, headaches, dry eyes, and fatigue. Poorly designed or heavy headsets can also cause neck strain and general physical discomfort. These risks are especially relevant in manufacturing environments, where workers may be required to wear the equipment throughout their shifts. User fatigue, especially from ill-fitting or poorly calibrated devices, has been identified as a persistent concern in industry deployments (ViewAR GmbH, 2023).
- **G1-1:** AR systems often include integrated cameras and sensors that continuously record and process environmental data to deliver augmented content. In manufacturing settings, this can result in persistent video capture of both the workplace and fellow employees. If this data is accessible to management, it may constitute a form of surveillance. Such practices raise serious ethical questions about autonomy and privacy. Continuous monitoring without explicit worker consent can undermine trust and create a culture of constant observation. Experts warn that without clear data governance and safeguards, AR use may violate privacy norms and erode employee well-being (Shore, 2025).

D.6.2. Digital manufacturing technologies at each digital maturity level and their negative impact for each ESRS impact

Table D.12: Digital maturity levels for digital manufacturing technologies and their negative impact for each ESRS impact.

ESRS	Digital Maturity Level				
	Descriptive	Diagnostic	Predictive	Prescriptive	Adaptive
E1-5	ERP requires continuous server uptime for basic operational visibility, increasing baseline electricity demand.	Comparing planned vs. actual system performance requires additional data logging and storage, straining infrastructure and raising energy use.	Running simulations and forecasting increases computational load, significantly boosting power demand.	Auto-generating optimized plans requires persistent, complex processing, further increasing IT energy consumption.	Real-time self-adjustments and integrations with shop floor data demand uninterrupted computing and cloud sync, peaking energy usage.
	Basic APS provides visibility of production schedules, requiring standard IT infrastructure with moderate energy use.	Diagnostic modules analyze delays and constraints, demanding more computing power and system uptime, increasing energy draw.	Predictive modeling adds complexity (e.g., Monte Carlo simulations, scenario forecasting), increasing server load and electricity usage.	Prescriptive tools rely on intensive optimization algorithms (e.g., linear programming), which significantly raise computing and energy demands.	Adaptive APS operates continuously, dynamically adjusting plans in real time, requiring maximum system uptime, data streaming, and processing power, greatly increasing energy consumption.

EDDC	Digital Maturity Level				
	Descriptive	Diagnostic	Predictive	Prescriptive	Adaptive
	HMIs run 24/7 to display KPIs and process status, contributing to constant power demand.	Trend logging and real-time analysis require larger screens and longer display time, increasing power draw and cooling needs in control rooms.	Predictive interfaces display alerts and simulations, using more advanced graphics and screen time, adding to energy load.	Prescriptive HMIs serve as control hubs, integrating with multiple systems, increasing data processing, brightness, and interface activity, raising total energy use.	N/A
	DCS components (controllers, terminals, network hardware) run 24/7, contributing significantly to base power load.	Diagnostic analytics increase sensor use and historian activity, expanding computational and server demands.	Predictive algorithms require more frequent data capture and modeling, leading to sustained high power use.	Prescriptive control strategies rely on advanced processing and real-time computation, raising power draw further.	Adaptive DCS operates autonomously across all loops, requiring continuous server and sensor activity, maximizing energy use and reducing efficiency without strict optimization policies.
	Basic cloud storage enables dashboards and mobile access by storing machine and sensor data, creating baseline demand for energy-intensive remote data centers.	Cross-system analytics and diagnostics increase data redundancy and transfer frequency between cloud servers, raising power usage and cooling needs.	Predictive models require massive, high-resolution datasets stored long-term, significantly increasing cloud storage volume, replication, and power use.	Prescriptive optimization at multiple sites increases real-time data exchange and computational load across distributed cloud systems, spiking energy demand.	Adaptive systems use continuous synchronization and coordination between edge and cloud layers, requiring constant data flow and maximized storage uptime, driving peak energy intensity in cloud infrastructure.
	Basic IIoT deployments involve dozens to hundreds of low-power devices (e.g. sensors, transmitters) that continuously collect and send data, increasing facility-wide power consumption.	Diagnostic-level IIoT adds local edge processors and analytics modules, increasing processing and communication loads and raising total energy use.	Predictive models require high-frequency sensing and computation at the edge, significantly elevating power draw across the network.	Prescriptive IIoT pushes constant updates and control instructions to machines, increasing communication intensity and energy needs for synchronization.	Adaptive IIoT creates continuous machine-to-machine coordination, requiring constant two-way data transmission and local AI execution, maximizing site-level power demand from distributed devices.
	Edge devices operate 24/7 across machines, drawing continuous power that contributes to a facility's baseline energy use.	Local analytics demand more processing power at the edge, increasing device energy draw and contributing to overall factory electricity usage.	Running predictive models on live data streams adds compute intensity to edge hardware, significantly raising power consumption.	Devices executing prescriptive actions in real time maintain high availability and data sync, further increasing total energy demands.	Fully autonomous edge coordination requires constant data processing, sensor fusion, and AI inference, maximizing continuous energy draw across a distributed device network.
	Logging historical process data to cloud databases results in continuous energy consumption in external data centers.	Diagnostic queries and analytics across large datasets require intensive computing and frequent data movement, increasing energy usage.	Predictive data lakes grow in scale to support model training, resulting in large-scale storage replication and compute-intensive processing.	Prescriptive optimization engines pull data continuously from distributed stores, maintaining high server loads.	Adaptive ML-based control systems stream and process massive real-time datasets 24/7, sustaining high cloud compute and storage energy draw.

EDDC	Digital Maturity Level				
	Descriptive	Diagnostic	Predictive	Prescriptive	Adaptive
	Continuous time-series data from sensors is streamed and stored in cloud-hosted data historians, adding to persistent energy loads.	Querying and replaying historical datasets for fault diagnosis increases compute and network traffic in data centers, raising energy use.	Feeding large datasets to ML pipelines (e.g. pattern detection) demands scalable cloud compute/storage infrastructure, significantly raising power use.	Prescriptive use integrates historian data with real-time optimizers (e.g. advanced scheduling tools), keeping data and compute layers always online.	Adaptive control relies on high-frequency historian updates to inform real-time ML models, creating always-on data ingestion, compute, and transmission: greatly increasing overall energy intensity.
	Basic on-prem connectivity (switches, access points, routers) runs 24/7 across the site, generating constant low-grade energy consumption.	Diagnostics require higher data throughput and more stable up-time, increasing the number of active connections and ports, raising cumulative energy use.	Predictive operations demand real-time data feeds from machines, increasing bandwidth usage and keeping more devices powered and active at all times.	Prescriptive logic requires seamless connectivity to push control actions rapidly across systems, stressing network reliability and increasing hardware load and power usage.	Adaptive CPS setups necessitate fully redundant, low-latency networks running nonstop, maximizing simultaneous device communication and locking in high total energy demand.
	Basic digital twins require constant data streaming, high-performance computing, and cloud access, increasing baseline electricity demand.	Diagnostic simulations (e.g. fault modeling) require extended compute time and data storage, raising power use from edge/cloud infrastructure.	Running “what-if” scenarios and physics-based models consumes significant computing resources, especially for high-fidelity simulations.	Prescriptive digital twins drive continuous bidirectional communication and optimization loops, increasing runtime and server loads.	Adaptive twins run autonomously, updating live parameters and synchronizing with real systems continuously, resulting in maximum energy use from AI, storage, and real-time compute operations.
	N/A	N/A	N/A	APC requires continuous operation of servers, sensors, and control algorithms, increasing base energy consumption from both computation and control equipment. If used to push processes harder (e.g., increase throughput), energy usage may rise faster than efficiency gains.	Adaptive APC runs machine learning-based controllers continuously and self-tunes in real time, maximizing energy demand across data processing, model training, and instrumentation infrastructure.
	MCTs use multiple displays, dashboards, cloud servers, and data streams, consuming significant energy even at the base monitoring level.	Analyzing downtime or delays across systems requires more frequent polling, server-side queries, and data processing, increasing digital power demand.	Forecasting mismatches and disruptions involves AI models and scenario simulations that increase compute loads across facilities and cloud networks.	Running prescriptive optimization (e.g. rerouting production) intensifies real-time computation and cross-site data syncing, further raising electricity use.	Adaptive control towers continuously analyze and coordinate production and logistics via AI, locking in high levels of energy consumption from edge-cloud systems, dashboards, and ML engines.

EDEC	Digital Maturity Level				
	Descriptive	Diagnostic	Predictive	Prescriptive	Adaptive
	Monitoring real-time metrics (OEE, defect rates) requires continuous sensor operation and computing infrastructure, adding steady power draw.	Diagnostic tools (control charts, variability drill-downs) require additional data processing and analytics, increasing IT and network energy load.	Forecasting drift and predictive quality control uses statistical models that require higher sampling rates and continuous computing, raising electricity use further.	Prescriptive SPC systems recommend changes based on real-time insights, increasing server use and control system communication.	Fully automated SPC continuously evaluates process variation and adjusts control loops autonomously, maintaining peak system activity and energy demand.
	AR headsets/tablets run continuously to display 3D process views or training content, adding to electricity use.	Diagnostic AR overlays (e.g., fault pinpointing) require more computing and camera use, raising network and processing energy.	Predictive simulations in AR (e.g., testing virtual design changes) demand high-performance computing, increasing cloud/IT load.	Prescriptive AR systems continuously run to push optimized work instructions to field devices, requiring sustained data sync and device uptime.	Adaptive AR requires real-time updates from AI systems, keeping all devices and cloud services running full time, significantly raising cumulative energy demand.
E1-6	Even basic ERP operation increases Scope 2 emissions due to the non-renewable portion of the energy grid.	Diagnostic insights require constant data polling and dashboard updates, indirectly raising GHG emissions.	Predictive capabilities amplify energy draw through simulations, expanding carbon impact unless grid fully green.	Prescriptive ERP modules may over-prioritize efficiency, paradoxically increasing runtime and total emissions.	Adaptive ERP operates continuously, auto-updating with high frequency, which can lock in a constant carbon-emitting power baseline.
	Electricity consumption from APS tools begins to contribute Scope 2 emissions depending on the energy mix.	Diagnostic analyses increase data processing frequency, expanding energy use and emissions indirectly.	Predictive functions intensify emissions as more compute-heavy simulations run around the clock.	Prescriptive tools may inadvertently increase energy use by prioritizing speed or cost over carbon efficiency.	Adaptive APS operates with constant feedback loops and recalculations, locking in high emissions unless green energy sources are prioritized, emissions scale with planning agility.
	Continuous HMI usage contributes to emissions via power drawn from fossil-fuel-intensive grids.	Increased data visualization and system polling for diagnostics raise electricity consumption, compounding indirect emissions.	Forecast-driven HMIs operate more interactively and require longer active screen time, amplifying emissions impact.	Command-and-control interfaces for prescriptive use create continuous computing loads, increasing Scope 2 emissions unless supported by clean energy.	N/A
	Constant DCS operation results in GHG emissions when powered by non-renewable sources.	Increased processing and historian usage in diagnostics raises indirect emissions.	Predictive DCS functions increase power use from simulations and early-warning systems, amplifying Scope 2 emissions.	Prescriptive logic may favor system performance or uptime over emissions reduction, potentially increasing overall plant power consumption.	Adaptive DCS systems draw heavily on always-on AI models and networked data flows, embedding high, consistent Scope 2 emissions into process control operations.

EDEC	Digital Maturity Level				
	Descriptive	Diagnostic	Predictive	Prescriptive	Adaptive
	Data center electricity consumption contributes indirectly to GHG emissions via fossil-fueled grid power.	Increased diagnostic computation extends usage duration and volume, intensifying Scope 2 emissions.	Training predictive models elevates computational intensity and storage usage, pushing GHG emissions higher unless powered by renewable sources.	Prescriptive cloud analytics rely on high-power, always-on infrastructure to drive optimization, compounding energy-related emissions.	Adaptive systems integrate edge-cloud networks and distributed AI agents, requiring persistent power from grid and backup systems, increasing Scope 1 (diesel) and Scope 2 emissions consistently.
	IIoT power usage contributes indirectly to GHG emissions when powered by a carbon-heavy grid.	Edge diagnostics increase device uptime and processing, intensifying indirect emissions.	Predictive systems may operate additional mobile or robotic devices (e.g., drones, AGVs), which introduce both battery charging emissions (Scope 2) and potential direct emissions if fuel-powered (Scope 1).	Real-time optimization may inadvertently keep equipment running more often, increasing Scope 2 emissions through constant coordination loops.	Fully autonomous IIoT systems amplify baseline emissions by operating with high redundancy, continuous connectivity, and maximum uptime, embedding emissions into every layer of factory operations.
	The electricity used by edge devices contributes to indirect GHG emissions from non-renewable grid sources.	Diagnostic analytics increase uptime and active device utilization, thereby intensifying Scope 2 emissions.	Predictive inference cycles consume more processing cycles and storage, expanding carbon footprints if not powered by clean energy.	Real-time control logic increases network-wide electricity use as devices continuously push commands, raising Scope 2 emissions.	Adaptive CPS-level edge systems create an “always-on” intelligent environment with high-frequency data loops, locking in high emissions across the entire edge infrastructure.
	Each read/write operation and storage update draws electricity from grids not fully decarbonized, increasing GHG emissions.	Constant diagnostics require data center operations to remain online at high capacity, raising emissions due to fossil-based energy sources.	Predictive analytics at scale (e.g., ML training) increase GPU/CPU usage and power demand, elevating GHG impact.	Prescriptive data applications keep infrastructure always-on to support optimization, sustaining electricity use with carbon consequences.	Adaptive systems enable real-time automation across facilities via cloud, locking in high emissions unless offset by green power sourcing.
	Cloud-hosted historians indirectly emit GHGs via non-renewable electricity powering data centers.	Diagnostic replay functions and analytics require continuous uptime for supporting IT systems, increasing cumulative emissions.	Predictive data historians require large-scale, low-latency compute that depends on fossil-based grid power unless fully offset.	Prescriptive use keeps historian-analytics loops active across shifts and geographies, expanding carbon footprints.	Adaptive use locks historian systems into 24/7 operation with backup power needs (diesel), increasing both Scope 2 and Scope 1 emissions.
	Continuous networking operations contribute to GHG emissions via electricity from fossil-fuel grids.	Diagnostics expand network activity with constant data transfer from edge to SCADA/MES, increasing indirect emissions.	Predictive functions may require parallel data streams (e.g., redundant routes, mirrored links) that increase total hardware use and associated Scope 2 emissions.	Prescriptive control architectures depend on high-availability connections (e.g., TSN or segmented networks), which can expand equipment count and power draw.	Adaptive coordination requires ultra-resilient, low-latency connectivity across factory systems, embedding round-the-clock emissions into the core infrastructure unless decarbonized.

CDC	Digital Maturity Level				
	Descriptive	Diagnostic	Predictive	Prescriptive	Adaptive
	Energy demands for real-time simulation and cloud storage translate into greenhouse gas emissions unless powered by green sources.	Simulations at diagnostic level increase indirect emissions through frequent system polling, live updates, and cloud-based analytics.	Predictive twins scale emissions as they operate intensively over time and across multiple machines/processes.	Prescriptive control loops require persistent server and system engagement, further increasing GHG output if energy is carbon-intensive.	Adaptive digital twins create continuous closed-loop feedback cycles, locking in large-scale Scope 2 emissions from real-time data acquisition, inference, and computation across sites.
	N/A	N/A	N/A	APC-related electricity consumption contributes to Scope 2 emissions. Moreover, if APC enables increased production volume without equivalent efficiency gains, Scope 1 emissions (e.g., process gases, thermal output) may also rise. Poorly tuned APC can worsen efficiency, causing instability or energy spikes.	Adaptive APC adjusts models constantly, which increases computational load and can cause frequent process shifts, potentially leading to more startups/shutdowns that increase emissions unless tightly optimized.
	Electricity powering the MCT's IT stack (cloud, edge, servers, monitors) contributes to Scope 2 emissions, especially on fossil-heavy grids.	Diagnostics expand processing demands and system uptime, amplifying indirect carbon emissions.	Predictive features run simulations frequently, further increasing emissions unless mitigated through renewables or energy-efficient architectures.	Real-time prescriptive outputs increase computational intensity across multiple systems and partners, compounding emissions.	Autonomous MCT operation requires full-system availability and compute at scale, entrenching digital emissions unless green computing strategies are in place.
	Powering SPC hardware and data networks increases Scope 2 emissions, especially with fossil-fuel-based electricity.	Diagnostic analysis adds emissions through continuous computing and control system uptime.	Predictive SPC increases emissions due to the always-on nature of monitoring and model computation.	Prescriptive recommendations create feedback loops that sustain high power use for real-time optimization.	Adaptive SPC systems require uninterrupted data flow, model training, and actuation, further entrenching indirect and (if climate-controlled rooms are used) direct emissions.
	Running AR platforms draws electricity from a grid that may still rely on fossil fuels, indirectly increasing emissions.	Diagnostic use adds to emissions as back-end systems stay online 24/7 to support AR content delivery.	Cloud-based predictive AR raises emissions further due to GPU-intensive computing and streaming requirements.	Prescriptive overlays pull real-time data across multiple systems, creating higher emissions via round-the-clock system use.	Adaptive AR with dynamic updates and automated visual instructions amplifies power use across both device and server infrastructure, heightening emissions.

CDC	Digital Maturity Level				
	Descriptive	Diagnostic	Predictive	Prescriptive	Adaptive
E2-4	MES-connected equipment (e.g., terminals, access points) keeps ambient systems (like cooling and backup generators) engaged more frequently.	Diagnostic MES tools increase background loads and uptime for auxiliary systems, indirectly increasing pollutant emissions.	Predictive MES anticipates spikes in equipment demand, which can trigger preemptive cooling or backup systems more often.	Prescriptive MES may cluster tasks for efficiency but unintentionally overload environmental control systems.	Adaptive MES perpetually balances machine usage, keeping all systems primed and often contributing to continuous auxiliary system operations, raising emissions.
	Redundant power systems (UPS, diesel gensets) for DCS increase the need for backup testing, releasing air pollutants (NOx, CO, particulates).	Diagnostics require consistent uptime, leading to more frequent genset tests and battery cycling, which can emit pollutants.	Predictive DCS models increase demand for power reliability, prompting more regular backup testing and pollutant output.	Prescriptive control strategies may increase dependency on uninterrupted control, tightening reliability margins and increasing pollution from redundancy infrastructure.	Adaptive DCS operates on edge-resilient networks requiring frequent failover and testing cycles, maximizing environmental impact from pollution-intensive support systems.
	Cloud data centers supporting manufacturing often maintain diesel generators, which emit air pollutants during testing or use.	More diagnostic services and uptime requirements increase testing frequency of backup generators, heightening localized pollution from NOx, CO, and particulates.	Predictive functions raise dependency on fault-tolerant systems, requiring more robust (and tested) diesel backup setups.	Multi-site prescriptive systems need high availability, often maintained through synchronized diesel gensets, amplifying the risk of pollution events during blackouts or grid instability.	Adaptive cloud-edge networks require ultra-reliable operations, leading to more frequent generator cycles and contributing cumulatively to local air quality degradation.
	Even simple data storage setups can require backup diesel generators, contributing to localized emissions during testing or outages.	Diagnostic analysis across historical data may require backup infrastructure for reliability, increasing generator readiness and emissions.	Predictive scale-out expands server farms, heightening reliance on backup systems and increasing local NOx and PM emissions.	Prescriptive systems necessitate low-latency access and high availability, increasing diesel generator testing frequency.	Adaptive infrastructure requires real-time resilience, potentially leading to greater use of backup systems with localized air quality implications.
	Each data center supporting historian functions maintains diesel generators that release NOx, CO, and particulate emissions during tests/outages.	Diagnostics require high uptime SLAs, meaning more regular backup system tests, adding to air quality concerns.	Predictive applications increase service criticality, prompting more frequent generator usage or testing, contributing to local air pollution.	Prescriptive systems often demand near-zero downtime, making sites more reliant on backup power systems.	Adaptive historian setups may require redundant global hosting and higher backup frequency, intensifying aggregate pollution effects.
	Initial ERP setup requires new terminals and server hardware, generating electronic waste.	Diagnostic expansion often triggers hardware upgrades for faster processing and analytics.	Predictive ERP demands high-performance infrastructure, accelerating obsolescence of older systems.	Frequent system recommendations push firms to upgrade ERP platforms and integrate additional tools, increasing hardware churn.	Adaptive ERP systems evolve rapidly, requiring ongoing hardware scalability and replacement, challenging circular economy goals.

EDC	Digital Maturity Level				
	Descriptive	Diagnostic	Predictive	Prescriptive	Adaptive
	Basic APS installs may require hardware upgrades (servers, terminals), generating some electronic waste.	Diagnostic expansion necessitates enhanced processing or storage, shortening the usable life of existing IT assets.	Predictive tools push firms to adopt advanced computational platforms, making older hardware obsolete.	Frequent updates to optimization modules or model libraries encourage rapid hardware cycling.	Adaptive APS requires top-tier, always-on systems that evolve with production, reinforcing a cycle of short-lived IT infrastructure and increasing e-waste burdens.
	Basic MES installs require terminals, sensors, and industrial PCs, starting the hardware turnover cycle.	Diagnostics require more sensors, higher-resolution data capture, and better displays, leading to quicker upgrades.	Predictive MES demands faster processors and smarter devices, accelerating the retirement of older units.	Prescriptive MES may require integrating new devices or platforms, pushing frequent system upgrades and incompatibility issues.	Adaptive MES relies on cutting-edge connectivity and responsive hardware, leading to constant evolution of tech stacks and high volumes of e-waste.
	Initial SCADA deployment involves new controllers, HMIs, and networking gear: hardware with eventual disposal impact.	Diagnostics often require higher-resolution or additional sensors, triggering early replacement of older units.	Predictive upgrades push for advanced PLCs or I/O modules with greater memory and processing speed, accelerating obsolescence.	Prescriptive SCADA may require sensor and actuator upgrades to support automated control suggestions, contributing to more device turnover.	Adaptive systems demand high-bandwidth wireless sensors, short-lifecycle batteries, and cutting-edge processors, significantly increasing e-waste and reducing circularity.
	Initial PLC installations add to e-waste as units reach end-of-life, especially if not recycled.	Diagnostic expansions often require controller upgrades for data handling and communication speed, reducing usable lifespans.	Predictive control demands higher processing capabilities, pushing organizations to retire functional but outdated PLCs prematurely.	Prescriptive control algorithms often need next-generation platforms (e.g. edge computing PLCs), accelerating turnover and increasing e-waste.	Adaptive control systems operate best on AI-compatible hardware, driving constant upgrades to maintain capability, which exacerbates e-waste volumes and disposal challenges.
	Even base-level DCS systems contribute substantial e-waste during upgrades (e.g. outdated controllers, I/O modules, servers).	Diagnostic tools often require newer hardware or firmware updates, accelerating turnover.	Predictive modeling needs more powerful processors and larger storage units, shortening system lifecycle and increasing e-waste.	Prescriptive systems mandate integration of modern, real-time computing platforms, prompting total system overhauls and large-scale disposal.	Adaptive DCS relies on continuous compatibility with AI-ready components, leading to regular upgrades of entire control cabinets and significant high-grade e-waste accumulation.
	Basic cloud services rely on servers with typical 3–5 year lifecycles; equipment aging leads to mounting e-waste.	Expanding analytics and diagnostics increase hardware demand, driving frequent server upgrades and replacements.	Predictive functions require higher storage performance and data throughput, encouraging rapid server hardware turnover.	Optimization workloads need cutting-edge processors and storage infrastructure, accelerating hardware obsolescence and cloud-driven e-waste.	Adaptive cloud infrastructure demands continuous compatibility and scale, creating an environment of constant hardware refresh cycles and substantial cumulative e-waste burdens.

ECDC	Digital Maturity Level				
	Descriptive	Diagnostic	Predictive	Prescriptive	Adaptive
	Even basic IIoT setups generate considerable e-waste from disposable or hard-to-recycle sensors and battery-operated devices.	Diagnostic tools may require denser sensor networks or newer device generations for analytics compatibility, driving frequent upgrades and disposal.	Predictive applications rely on high-fidelity sensing, pushing companies to replace older or low-precision sensors with more sophisticated but short-lived units.	Prescriptive IIoT systems demand reliable, high-bandwidth components with edge computing features, accelerating device churn and contributing to WEEE.	Adaptive IIoT architectures involve tightly integrated CPS (cyber-physical systems) that require frequent hardware refresh cycles, resulting in continuous accumulation of small, hard-to-track e-waste.
	Even basic edge deployments lead to e-waste accumulation, especially from small, embedded units often discarded casually.	Diagnostics often require higher-fidelity sensing or faster processors, triggering hardware upgrades and early device replacement.	Predictive processing accelerates obsolescence as more capable chips are needed to maintain inference accuracy and speed.	Devices used for prescriptive control must integrate with advanced protocols, leading to compatibility-driven turnover of earlier generations.	Adaptive edge networks require continuous compatibility with AI platforms and dynamic reconfiguration, driving frequent refresh cycles and significantly worsening e-waste generation from small devices.
	Servers used for descriptive data storage are replaced every few years, generating ongoing electronic waste.	More intensive diagnostics may require hardware upgrades or expansion, resulting in faster turnover of compute and network equipment.	Growth in predictive modeling encourages deployment of high-performance machines, increasing component replacement cycles.	Prescriptive AI engines drive demand for newer hardware to maintain speed and accuracy, worsening e-waste accumulation.	Adaptive control demands cutting-edge servers and high redundancy, causing accelerated hardware obsolescence and greater disposal volumes.
	Historian hardware (e.g. time-series databases in cloud servers) typically have 3–5 year refresh cycles.	Diagnostic needs may prompt expansion of clusters or faster hardware to speed data queries, accelerating device obsolescence.	Predictive workloads (especially when feeding ML tools) drive rapid scaling and upgrading of server hardware.	Prescriptive tools demand low-latency, high-performance historian integration, causing continuous updates of network and compute systems.	Adaptive historian systems use edge-cloud sync and high-frequency redundancy, creating extensive, distributed e-waste streams unless circular strategies are in place.
	Even basic network changes (e.g., upgrading switches or access points) contribute to gradual e-waste accumulation.	Diagnostics require more sophisticated switches, media converters, and cabling to support high-speed communication and diagnostics protocols.	Predictive capabilities often force transition to real-time industrial Ethernet or higher-capacity infrastructure, resulting in disposal of legacy equipment.	Prescriptive use pushes upgrades to ultra-low-latency networking, which may require specialized gear and compatibility retrofits, generating more obsolete components.	Adaptive connectivity requires edge-aligned, high-precision networks with tight time coordination, leading to short refresh cycles and a substantial increase in waste from cables, switches, and interface hardware.

EDC	Digital Maturity Level				
	Descriptive	Diagnostic	Predictive	Prescriptive	Adaptive
	Maintaining an accurate twin requires frequent hardware refresh (e.g. updated sensors, PLCs, or edge devices), contributing to e-waste.	Diagnostic expansion demands higher-fidelity input data, prompting premature replacement of older, less precise devices.	Predictive twins drive upgrades in compute infrastructure (e.g. GPU servers, edge accelerators), increasing turnover and discarded electronics.	Prescriptive use pressures organizations to replace legacy systems incompatible with digital twin integration, worsening hardware obsolescence.	Adaptive digital twins evolve in sync with physical systems, requiring continuous upgrades of compute, sensing, and networking tech, resulting in a significant and persistent stream of e-waste.
	N/A	N/A	N/A	Deployment of APC often requires upgrading legacy PLCs and analog instruments, which generates significant e-waste. High-accuracy sensors may need frequent recalibration or replacement, contributing to small-device e-waste streams.	Adaptive APC requires advanced, often proprietary sensors and model-capable devices, which accelerate obsolescence and expand electronic waste volume due to compatibility or performance constraints.
	Control tower deployment involves dashboards, servers, sensors, and connectors, each with a limited lifecycle, contributing to e-waste.	Expanding diagnostic coverage requires newer, faster interfaces and upgraded hardware, shortening replacement cycles.	Predictive capabilities need high-performance compute infrastructure, often replacing existing tools, increasing e-waste volumes.	Prescriptive MCTs prioritize speed and service continuity, potentially at the cost of circularity (e.g., tolerating more material waste or scrapping surplus stock).	Adaptive control towers evolve with AI and automation platforms, driving continual hardware refresh and risk overlooking material efficiency if not explicitly configured with circularity metrics.
	Even basic SPC setups lead to sensor and device waste over time, particularly if monitoring is scaled broadly.	Diagnostics often drive replacement of outdated or low-precision components, contributing to scrapped instruments and control hardware.	Predictive SPC needs high-quality, high-speed sensing and computing, shortening the usable life of older devices and increasing e-waste.	Prescriptive systems require seamless system integration, prompting upgrades across control and data handling layers.	Adaptive SPC demands highly accurate, AI-compatible hardware, leading to frequent component refresh cycles and escalating electronic waste volumes.
	Headsets and tablets have short upgrade cycles and limited modularity, leading to frequent disposal.	Diagnostic AR integration may force compatibility-driven upgrades (e.g., cameras or sensors not supported on older devices).	High-performance predictive AR often demands newer models with better specs, increasing hardware obsolescence.	Prescriptive AR involves continuous use and tight integration, hastening wear-out and driving faster replacement rates.	Adaptive AR relies on cutting-edge hardware and constant sensor calibration, driving up both waste volume and the challenge of proper recycling.
	Initial ERP setup requires new terminals and server hardware, generating electronic waste.	Diagnostic expansion often triggers hardware upgrades for faster processing and analytics.	Predictive ERP demands high-performance infrastructure, accelerating obsolescence of older systems.	Frequent system recommendations push firms to upgrade ERP platforms and integrate additional tools, increasing hardware churn.	Adaptive ERP systems evolve rapidly, requiring ongoing hardware scalability and replacement, challenging circular economy goals.

EDC	Digital Maturity Level				
	Descriptive	Diagnostic	Predictive	Prescriptive	Adaptive
	Basic APS installs may require hardware upgrades (servers, terminals), generating some electronic waste.	Diagnostic expansion necessitates enhanced processing or storage, shortening the usable life of existing IT assets.	Predictive tools push firms to adopt advanced computational platforms, making older hardware obsolete.	Frequent updates to optimization modules or model libraries encourage rapid hardware cycling.	Adaptive APS requires top-tier, always-on systems that evolve with production, reinforcing a cycle of short-lived IT infrastructure and increasing e-waste burdens.
	Basic MES installs require terminals, sensors, and industrial PCs, starting the hardware turnover cycle.	Diagnostics require more sensors, higher-resolution data capture, and better displays, leading to quicker upgrades.	Predictive MES demands faster processors and smarter devices, accelerating the retirement of older units.	Prescriptive MES may require integrating new devices or platforms, pushing frequent system upgrades and incompatibility issues.	Adaptive MES relies on cutting-edge connectivity and responsive hardware, leading to constant evolution of tech stacks and high volumes of e-waste.
	Initial SCADA deployment involves new controllers, HMIs, and networking gear: hardware with eventual disposal impact.	Diagnostics often require higher-resolution or additional sensors, triggering early replacement of older units.	Predictive upgrades push for advanced PLCs or I/O modules with greater memory and processing speed, accelerating obsolescence.	Prescriptive SCADA may require sensor and actuator upgrades to support automated control suggestions, contributing to more device turnover.	Adaptive systems demand high-bandwidth wireless sensors, short-lifecycle batteries, and cutting-edge processors, significantly increasing e-waste and reducing circularity.
	Initial PLC installations add to e-waste as units reach end-of-life, especially if not recycled.	Diagnostic expansions often require controller upgrades for data handling and communication speed, reducing usable lifespans.	Predictive control demands higher processing capabilities, pushing organizations to retire functional but outdated PLCs prematurely.	Prescriptive control algorithms often need next-generation platforms (e.g. edge computing PLCs), accelerating turnover and increasing e-waste.	Adaptive control systems operate best on AI-compatible hardware, driving constant upgrades to maintain capability, which exacerbates e-waste volumes and disposal challenges.
	Even base-level DCS systems contribute substantial e-waste during upgrades (e.g. outdated controllers, I/O modules, servers).	Diagnostic tools often require newer hardware or firmware updates, accelerating turnover.	Predictive modeling needs more powerful processors and larger storage units, shortening system lifecycle and increasing e-waste.	Prescriptive systems mandate integration of modern, real-time computing platforms, prompting total system overhauls and large-scale disposal.	Adaptive DCS relies on continuous compatibility with AI-ready components, leading to regular upgrades of entire control cabinets and significant high-grade e-waste accumulation.
	Basic cloud services rely on servers with typical 3–5 year lifecycles; equipment aging leads to mounting e-waste.	Expanding analytics and diagnostics increase hardware demand, driving frequent server upgrades and replacements.	Predictive functions require higher storage performance and data throughput, encouraging rapid server hardware turnover.	Optimization workloads need cutting-edge processors and storage infrastructure, accelerating hardware obsolescence and cloud-driven e-waste.	Adaptive cloud infrastructure demands continuous compatibility and scale, creating an environment of constant hardware refresh cycles and substantial cumulative e-waste burdens.

EDEC	Digital Maturity Level				
	Descriptive	Diagnostic	Predictive	Prescriptive	Adaptive
	Even basic IIoT setups generate considerable e-waste from disposable or hard-to-recycle sensors and battery-operated devices.	Diagnostic tools may require denser sensor networks or newer device generations for analytics compatibility, driving frequent upgrades and disposal.	Predictive applications rely on high-fidelity sensing, pushing companies to replace older or low-precision sensors with more sophisticated but short-lived units.	Prescriptive IIoT systems demand reliable, high-bandwidth components with edge computing features, accelerating device churn and contributing to WEEE.	Adaptive IIoT architectures involve tightly integrated CPS (cyber-physical systems) that require frequent hardware refresh cycles, resulting in continuous accumulation of small, hard-to-track e-waste.
	Even basic edge deployments lead to e-waste accumulation, especially from small, embedded units often discarded casually.	Diagnostics often require higher-fidelity sensing or faster processors, triggering hardware upgrades and early device replacement.	Predictive processing accelerates obsolescence as more capable chips are needed to maintain inference accuracy and speed.	Devices used for prescriptive control must integrate with advanced protocols, leading to compatibility-driven turnover of earlier generations.	Adaptive edge networks require continuous compatibility with AI platforms and dynamic reconfiguration, driving frequent refresh cycles and significantly worsening e-waste generation from small devices.
	Servers used for descriptive data storage are replaced every few years, generating ongoing electronic waste.	More intensive diagnostics may require hardware upgrades or expansion, resulting in faster turnover of compute and network equipment.	Growth in predictive modeling encourages deployment of high-performance machines, increasing component replacement cycles.	Prescriptive AI engines drive demand for newer hardware to maintain speed and accuracy, worsening e-waste accumulation.	Adaptive control demands cutting-edge servers and high redundancy, causing accelerated hardware obsolescence and greater disposal volumes.
	Historian hardware (e.g. time-series databases in cloud servers) typically have 3–5 year refresh cycles.	Diagnostic needs may prompt expansion of clusters or faster hardware to speed data queries, accelerating device obsolescence.	Predictive workloads (especially when feeding ML tools) drive rapid scaling and upgrading of server hardware.	Prescriptive tools demand low-latency, high-performance historian integration, causing continuous updates of network and compute systems.	Adaptive historian systems use edge-cloud sync and high-frequency redundancy, creating extensive, distributed e-waste streams unless circular strategies are in place.
	Even basic network changes (e.g., upgrading switches or access points) contribute to gradual e-waste accumulation.	Diagnostics require more sophisticated switches, media converters, and cabling to support high-speed communication and diagnostics protocols.	Predictive capabilities often force transition to real-time industrial Ethernet or higher-capacity infrastructure, resulting in disposal of legacy equipment.	Prescriptive use pushes upgrades to ultra-low-latency networking, which may require specialized gear and compatibility retrofits, generating more obsolete components.	Adaptive connectivity requires edge-aligned, high-precision networks with tight time coordination, leading to short refresh cycles and a substantial increase in waste from cables, switches, and interface hardware.

CDC	Digital Maturity Level				
	Descriptive	Diagnostic	Predictive	Prescriptive	Adaptive
	Maintaining an accurate twin requires frequent hardware refresh (e.g. updated sensors, PLCs, or edge devices), contributing to e-waste.	Diagnostic expansion demands higher-fidelity input data, prompting premature replacement of older, less precise devices.	Predictive twins drive upgrades in compute infrastructure (e.g. GPU servers, edge accelerators), increasing turnover and discarded electronics.	Prescriptive use pressures organizations to replace legacy systems incompatible with digital twin integration, worsening hardware obsolescence.	Adaptive digital twins evolve in sync with physical systems, requiring continuous upgrades of compute, sensing, and networking tech, resulting in a significant and persistent stream of e-waste.
	N/A	N/A	N/A	Deployment of APC often requires upgrading legacy PLCs and analog instruments, which generates significant e-waste. High-accuracy sensors may need frequent recalibration or replacement, contributing to small-device e-waste streams.	Adaptive APC requires advanced, often proprietary sensors and model-capable devices, which accelerate obsolescence and expand electronic waste volume due to compatibility or performance constraints.
	Control tower deployment involves dashboards, servers, sensors, and connectors, each with a limited lifecycle, contributing to e-waste.	Expanding diagnostic coverage requires newer, faster interfaces and upgraded hardware, shortening replacement cycles.	Predictive capabilities need high-performance compute infrastructure, often replacing existing tools, increasing e-waste volumes.	Prescriptive MCTs prioritize speed and service continuity, potentially at the cost of circularity (e.g., tolerating more material waste or scrapping surplus stock).	Adaptive control towers evolve with AI and automation platforms, driving continual hardware refresh and risk overlooking material efficiency if not explicitly configured with circularity metrics.
	Even basic SPC setups lead to sensor and device waste over time, particularly if monitoring is scaled broadly.	Diagnostics often drive replacement of outdated or low-precision components, contributing to scrapped instruments and control hardware.	Predictive SPC needs high-quality, high-speed sensing and computing, shortening the usable life of older devices and increasing e-waste.	Prescriptive systems require seamless system integration, prompting upgrades across control and data handling layers.	Adaptive SPC demands highly accurate, AI-compatible hardware, leading to frequent component refresh cycles and escalating electronic waste volumes.
	Headsets and tablets have short upgrade cycles and limited modularity, leading to frequent disposal.	Diagnostic AR integration may force compatibility-driven upgrades (e.g., cameras or sensors not supported on older devices).	High-performance predictive AR often demands newer models with better specs, increasing hardware obsolescence.	Prescriptive AR involves continuous use and tight integration, hastening wear-out and driving faster replacement rates.	Adaptive AR relies on cutting-edge hardware and constant sensor calibration, driving up both waste volume and the challenge of proper recycling.
	Continuous use of ERP systems can cause eyestrain and repetitive stress from desk-based work.	Diagnostic insights raise performance visibility, potentially increasing stress from tighter monitoring.	Predictive alerts can create anxiety by emphasizing future risks or inefficiencies beyond workers' control.	Prescriptive outputs may introduce pressure to act quickly on system-generated advice, leading to decision fatigue or perceived loss of agency.	Adaptive systems drive constant system responsiveness, promoting a high-pressure environment where performance is tracked and adjusted without worker discretion.
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CDC	Digital Maturity Level				
	Descriptive	Diagnostic	Predictive	Prescriptive	Adaptive
	Basic APS use may lengthen screen time and increase digital engagement, introducing low-level ergonomic strain.	Diagnostic pressure to interpret and act on bottleneck data creates additional decision stress for planners.	Predictive alerts about future risks add cognitive burden, especially if forecasts are uncertain or difficult to control.	Prescriptive schedules might appear overly rigid or aggressive, raising stress for operators trying to meet algorithm-generated targets.	Adaptive APS constantly changes plans in real time, creating an environment of unpredictability and continuous urgency, raising stress and reducing perceived control.
	Workers using MES terminals face increased screen time, contributing to minor ergonomic and vision issues.	Frequent diagnostic alerts and warnings increase cognitive load and stress, especially when linked to performance tracking.	Predictive MES escalates pressure by forecasting future problems or quality risks, potentially overwhelming operators.	Prescriptive MES issues automated instructions, limiting worker discretion and potentially increasing tension on the floor.	Adaptive MES continuously issues updates and changes in real time, potentially leading to alert fatigue, loss of situational awareness, and increased stress or error risk.
	SCADA-controlled systems may fail in ways that jeopardize worker safety (e.g., incorrect sensor input causing misactuation).	Diagnostic tools may shift attention to digital data rather than physical inspection, increasing reliance on SCADA even when sensor accuracy may degrade.	Predictive warnings can reduce preventive maintenance windows if staff overtrust system accuracy, potentially increasing process risk.	Prescriptive SCADA may automate decisions without ground-level human confirmation, raising danger of unexpected machine actions.	Adaptive SCADA continuously modifies process conditions: if not tightly supervised, this can expose operators to unsafe, unpredictable behavior from equipment.
	Basic PLC operation removes workers from physical hazards but increases screen-based monitoring.	Diagnostic tasks require more frequent HMI interaction and control tuning, increasing sedentary work and eyestrain.	Predictive feedback and alert trends create pressure on staff to anticipate failures or explain algorithmic decisions.	Prescriptive PLCs dictate actions based on model outputs, reducing autonomy and fragmenting work into response cycles.	Adaptive PLCs make real-time control decisions without human intervention, which can alienate workers, erode job satisfaction, and lead to stress due to lack of perceived control.
	Continuous HMI monitoring creates strain on eyes, neck, and posture, especially if poorly positioned.	Diagnostic interactions (e.g. log analysis) lengthen screen time and promote sedentary work, increasing physical health risks.	Predictive HMIs generate more alerts and require proactive attention, contributing to vigilance fatigue and stress.	Prescriptive HMI interfaces drive fast-paced decision-making under pressure, increasing stress and anxiety, especially in alarm-heavy environments.	N/A
	Base-level DCS places responsibility on operators for continuous monitoring, errors can have major consequences.	Diagnostics produce layered alarms and event reports, increasing alert fatigue and decision stress.	Predictive warnings and failure forecasts place operators under pressure to act early and often, raising anxiety.	Prescriptive control systems can override human discretion, creating tension and reducing perceived operator control.	Adaptive systems automate most decisions, leaving humans in a passive supervisory role with high stakes but low agency, intensifying job-related stress.

ECDC	Digital Maturity Level				
	Descriptive	Diagnostic	Predictive	Prescriptive	Adaptive
	Basic edge devices gather data with limited control capabilities, posing low safety risks directly.	Diagnostic features introduce semi-automated actions based on anomaly detection, which if inaccurate, could initiate unsafe responses.	Predictive devices act on forecasted behavior and can misinterpret trends, potentially triggering premature or incorrect actions.	Prescriptive edge control increases automation of real-time actions, raising the chance of critical process errors if the logic is flawed.	Fully autonomous devices operating as local AI agents can make complex decisions without human oversight, introducing systemic safety risks from misinterpretation or cascading errors across systems.
	Monitoring a live digital twin requires frequent interpretation of data dashboards and alerts, which can cause mental strain.	Diagnostic twins increase the quantity and complexity of information workers must analyze (e.g. simulations, scenario data).	Predictive systems demand rapid interpretation of multi-variable forecasts, which can overwhelm less digitally skilled staff.	Prescriptive twins generate real-time optimization outputs that operators may need to validate under pressure, creating cognitive stress.	Adaptive twins automate decision cycles, requiring constant monitoring for exception handling, further intensifying psychological burden for staff who must oversee autonomous systems.
	N/A	N/A	N/A	Operators shift from active control to passive oversight, which may reduce engagement. In rare failures, the “automation paradox” can cause delayed or incorrect human response if operators are unprepared to retake control. Complex APC software may display unclear messages that delay decision-making during critical events.	Adaptive APC changes control logic dynamically. If operators are not continuously trained or integrated into the decision cycle, they may lack awareness or understanding of the system’s actions, increasing cognitive stress and safety risk in exception scenarios.
	Even at basic levels, MCT work involves long screen hours, leading to eye strain, sedentary stress, and mild ergonomic risks.	As diagnostics add real-time fault identification, staff must monitor and interpret complex dashboards, increasing cognitive load.	Predictive disruption alerts elevate pressure to preemptively act on uncertain scenarios, intensifying psychological stress.	Prescriptive decisions often carry high stakes (e.g. rebalancing entire inventory plans), with staff held accountable, raising anxiety and fatigue.	Adaptive MCTs automate decisions but still require human oversight during exceptions; the combination of minimal control and high responsibility can lead to sustained mental strain.
	Operators monitor dashboards for process deviations; constant vigilance can increase cognitive load and fatigue.	Diagnostic alarms (e.g. out-of-control signals) create pressure to act quickly, which can heighten anxiety and mental strain.	Predictive SPC increases tension by forecasting upcoming deviations, pushing workers to act preemptively under uncertainty.	Prescriptive SPC recommendations must be interpreted and validated under time pressure, increasing psychological strain and the risk of over-reliance on system guidance.	Adaptive SPC bypasses operators entirely, which may reduce situational awareness and job satisfaction, especially in high-stakes environments, exacerbating trust and accountability stress.

CDC	Digital Maturity Level				
	Descriptive	Diagnostic	Predictive	Prescriptive	Adaptive
	Continuous AR use may cause eyestrain, visual fatigue, and discomfort from poorly fitted headsets.	Diagnostic AR requires operators to look closely and move in specific ways, which can lead to repetitive strain or headaches.	Predictive use increases exposure time and reliance on heavy headgear, amplifying physical fatigue and posture risks.	Prescriptive AR often requires following visual overlays during physical tasks, raising risks of distraction or injury if overlays misalign or glitch.	Adaptive AR may shift control away from workers entirely, reducing situational awareness and potentially creating unsafe blind reliance on system-generated instructions.
S1-15	Always-on ERP infrastructure makes after-hours data access easy, encouraging off-shift check-ins.	Diagnostic tools drive demand for timely analysis, prompting late-night data reviews and reporting.	Predictive models operate across global schedules, nudging staff to monitor outcomes beyond normal hours.	Prescriptive ERP alerts can trigger off-shift actions to comply with optimized workflows or resolve flagged issues.	Adaptive ERP perpetuates a real-time, always-connected culture, breaking down clear boundaries between work and personal time.
	Early APS stages already promote 24/7 data visibility, tempting off-shift checking by planners or managers.	Diagnostic modules raise expectations for late-night analysis or alert reviews to resolve delays faster.	Predictive tools may operate overnight, with alerts or reports surfacing at odd hours, requiring off-shift engagement.	Prescriptive APS can change plans frequently and close to deadlines, demanding last-minute responses beyond normal working hours.	Adaptive APS blurs work boundaries entirely, as system-triggered replanning and alerts can occur any time, pressuring staff to stay always connected.
	MES dashboards remain accessible after shifts, tempting staff to monitor statuses or complete logs outside work hours.	Diagnostic MES tools create expectations for round-the-clock issue resolution, expanding work into personal time.	Predictive MES may alert managers to potential disruptions at any hour, prompting off-shift reviews or preemptive interventions.	Prescriptive systems issue rapid updates requiring immediate action, making off-hour engagement feel necessary.	Adaptive MES auto-triggers changes and alerts at any time, normalizing 24/7 availability and weakening boundaries between work and personal life.
	Basic SCADA requires personnel to monitor process alarms around the clock, initiating early strains on personal time.	Diagnostic tools generate frequent alerts for trend anomalies, often requiring night-time login or physical presence.	Predictive SCADA increases alarm volume through forecasting, generating more out-of-hours interventions.	Prescriptive functionality automates decision-making but still often requires operator verification at all hours.	Adaptive SCADA self-operates but still notifies staff of exceptions immediately, enforcing a "perpetual availability" culture with 24/7 responsiveness.
	PLC networks operate 24/7, creating expectations for after-hours monitoring or alarm response.	Diagnostic tools generate alerts and performance logs that may require engineers to review or act during off hours.	Predictive PLC models forecast issues in real time, pressuring staff to remain available for validation or intervention at all times.	Prescriptive control loops may initiate actions needing confirmation or review during non-shift hours, adding to digital overwork.	Adaptive PLCs function autonomously but still flag anomalies or require human verification on exception events, embedding a culture of constant availability among automation staff.
	DCS systems support 24/7 monitoring, requiring off-shift staff availability for alarms or troubleshooting.	Diagnostic modules generate logs and reports that often require after-hours access and responses.	Predictive alerts can notify staff of future risks anytime, increasing remote engagement expectations.	Prescriptive controls may require engineer input even after-hours to approve overrides or verify actions.	Adaptive DCS continuously evaluates systems and notifies staff of exceptions immediately, enforcing a constant availability culture and eroding work-life boundaries.

CDC	Digital Maturity Level				
	Descriptive	Diagnostic	Predictive	Prescriptive	Adaptive
	Basic cloud dashboards make production data available anytime via mobile or web access, increasing the temptation for after-hours engagement.	Diagnostic tools deliver alert histories or exception logs directly to personal devices, encouraging work during non-shift hours.	Predictive alerts may generate proactive notifications based on forecasts, driving off-hour attention to preemptive insights.	Prescriptive analytics require timely interventions based on automated recommendations, pressuring staff to remain connected to interpret or act outside formal work hours.	Adaptive systems operate seamlessly in real time across global factory networks, normalizing a “hyper-connected” culture and heavily blurring personal-professional boundaries with persistent availability expectations.
	Workers may feel pressure to check dashboards or log data remotely at all hours due to easy mobile/cloud access.	Diagnostic tools available 24/7 increase expectations for off-hours troubleshooting or data review.	Predictive model performance monitoring may lead to out-of-hours alerts for data scientists or engineers.	Prescriptive analytics tools drive real-time decisions, pressuring staff to remain available to validate or intervene.	Adaptive closed-loop systems operate nonstop, prompting employees to be reachable constantly to oversee or audit decisions, undermining rest time.
	Historian data, once cloud-hosted, is accessible 24/7, prompting off-hours engagement by staff (e.g., data engineers or quality teams).	Diagnostic use may lead to alerts or review requests beyond shifts, pressuring staff to respond on-demand.	Predictive failure models using historian data might alert users to patterns at any time, raising expectations for real-time response.	Prescriptive control systems require ongoing validation, drawing employees into reactive cycles regardless of working hours.	Adaptive historian systems may alert or auto-adjust without warning, and engineers might be expected to audit or override outputs from remote, further blurring work/personal time boundaries.
	Even simple twins can run 24/7, delivering alerts and insights at all hours, encouraging off-shift engagement.	Diagnostic twins produce trend and anomaly notifications that often require timely human validation, prompting after-hours logins.	Predictive models create forecast-driven alerts across time zones and shift schedules, reducing employee downtime.	Prescriptive optimization pushes changes in real time, with staff expected to validate or respond outside core work hours.	Adaptive digital twins run autonomously, issuing updates and decisions around the clock, blurring work boundaries and promoting an “always-on” digital monitoring culture.
	N/A	N/A	N/A	APC’s always-on nature increases off-shift alerting and troubleshooting expectations. Engineers may feel compelled to remain connected remotely at all times to respond to control issues, eroding personal time and rest periods.	Adaptive APC increases alert complexity and frequency (e.g., model divergence, exception handling), which can lead to engineers being on-call 24/7 for oversight of continuously updating AI models.

CDC	Digital Maturity Level				
	Descriptive	Diagnostic	Predictive	Prescriptive	Adaptive
	Monitoring across time zones extends shifts and creates 24/7 expectations for even non-operations roles (e.g., planners, analysts).	Diagnosing cross-site problems often requires late-night or off-hour involvement, blurring boundaries between work and personal time.	Predictive alerts (e.g. demand surges or equipment failures) can surface at any time, pressuring staff to engage outside their core hours.	Prescriptive rerouting or scheduling decisions may demand immediate validation, leading to off-shift interventions.	Adaptive MCTs push live decisions continuously, creating a culture where teams must monitor exceptions and updates at all hours, deepening work-life erosion.
G1-1	Even basic ERP logs all transactions, building datasets that could expose user activity patterns.	Diagnostic tools trace activity to individual users, increasing perceptions of surveillance.	Predictive ERP may anticipate errors or underperformance, raising fears of preemptive judgment or monitoring.	Prescriptive recommendations may be used to enforce rigid behavior norms, especially if decisions are based on detailed usage logs.	Adaptive ERP automates decisions using live employee data, making privacy and autonomy concerns systemic and difficult to audit.
	Basic APS begins to centralize decisions in software, reducing worker visibility into scheduling logic.	Diagnostic suggestions may shift blame for inefficiencies onto users or operators, affecting morale.	Predictive models can embed bias (e.g., always predicting lower performance for certain shifts), reducing trust in APS outputs.	Prescriptive APS may enforce decisions without consulting affected staff, supporting resentment or alienation.	Adaptive systems automate trade-offs between productivity and fairness without transparency, creating ethical dilemmas and risks of digital authoritarianism in scheduling.
	MES logs user actions at terminals, enabling visibility into task completion times and operator behavior.	Diagnostic tracking can be used to identify perceived underperformance, raising feelings of surveillance among staff.	Predictive MES extrapolates behavior trends, raising fear that workers will be judged on projected performance.	Prescriptive MES ties task instructions directly to performance metrics, allowing management to intervene without context or transparency.	Adaptive MES autonomously monitors and adjusts operations using live worker data, embedding a surveillance dynamic deeply into shop floor routines.
	SCADA tracks all user interactions with HMIs and process interfaces, beginning basic surveillance.	Diagnostic systems enable detailed logs of operator actions, timings, and reactions to alarms, expanding visibility into individual performance.	Predictive SCADA can be used to assess worker efficiency or anticipate errors, leading to perceived micro-management.	Prescriptive SCADA actions may override worker judgment, reducing autonomy and accountability, and shifting control to opaque system rules.	Adaptive SCADA relies on real-time employee data to inform autonomous processes, embedding constant behavioral monitoring into operational routines, raising ethical and morale concerns.
	Basic HMI systems record operator actions (e.g. alarm acknowledgement times), which can be used to monitor performance.	Diagnostic logging expands traceability of user decisions and mistakes, raising surveillance concerns.	Predictive HMIs may analyze individual operator responses to alerts or trends, indirectly profiling performance or predicting future error risk.	Prescriptive systems may log how and when operators accept/reject system-suggested actions, embedding deeper surveillance into human-machine interactions.	N/A

EDDC	Digital Maturity Level				
	Descriptive	Diagnostic	Predictive	Prescriptive	Adaptive
	DCS logs every operator interaction, creating visibility that can be misused for performance scrutiny.	Diagnostic tools extend traceability of control actions and fault responses, increasing the risk of unjust blame.	Predictive insights may profile operator behavior or effectiveness, potentially influencing staffing decisions.	Prescriptive systems might automatically flag deviations or ignore contextual human judgment, causing resentment or distrust.	Adaptive DCS embeds surveillance into routine operation, as AI monitors and reacts to all user actions, raising transparency and fairness concerns if not managed ethically.
	Edge devices record large volumes of process and operational data, some of which may include indirect worker behavior metrics.	Diagnostic analytics increase detail granularity and retention of device-level logs, expanding potential exposure of sensitive workplace data.	Predictive edge systems analyze patterns that may inadvertently identify worker behavior trends or decision speed, raising ethical concerns.	Prescriptive actions driven by edge data could be linked to individual outcomes (e.g., tying machine error rates to operators), reinforcing surveillance dynamics.	Adaptive systems constantly evaluate performance inputs across workers and machines in real time, embedding surveillance into everyday operations and raising complex ethical risks around transparency, consent, and data use.
	N/A	N/A	N/A	APC can automate many manual control tasks, reducing the need for certain operator or technician roles. Without fair labor policies or retraining, it may lead to layoffs or worker disengagement.	Adaptive APC, with self-learning and autonomous control, may remove even more human oversight roles. If not implemented ethically, this can create structural inequality, leaving displaced workers without digital reskilling opportunities.
	MCTs consolidate granular machine and operator data, potentially including task durations, shift logs, and performance metrics.	Diagnostics link outcomes directly to operator actions or locations, raising concerns about over-monitoring and transparency.	Predictive tools can infer future behaviors or risks tied to specific workers or lines, creating profiling and fairness risks.	Prescriptive systems act on worker-linked data to adjust plans, which may feel intrusive or controlling without proper safeguards.	Adaptive MCTs rely on pervasive sensing and real-time human-machine feedback, embedding surveillance deeply into operations unless managed with strong privacy and consent protocols.
	AR devices collect visual and sensor data of the workplace, potentially capturing coworkers and sensitive operations.	Diagnostic use might involve video logging of faults, which could be reviewed by supervisors, raising employee privacy issues.	Predictive models may use performance data in ways not transparent to workers, reinforcing monitoring culture.	Prescriptive systems feed worker responses into central analytics, possibly enabling micro-monitoring of compliance.	Adaptive AR bots could create continuous, AI-mediated surveillance if ethical safeguards aren't built in, deeply impacting worker autonomy and trust.

D.6.3. Trade-offs for digital manufacturing technologies for ESRS impacts

Table D.13: Overview of for which of the selected digital manufacturing technologies relevant to the Dutch high-tech manufacturing sector there is a trade-off for the ESRS impact categories.

Digital manufacturing technology	E1-5 (Energy consumption and mix)	E1-6 (GHG emissions)	E2-4 (Air pollution)	E5-5 (Waste & circularity)	S1-9 (Diversity & inclusion)	S1-13 (Training & skills)	S1-14 (Occupation health & safety)	S1-15 (Work-life balance)	G1-1 (Ethical culture and behavior)
ERP (enterprise resource planning)	X	X		X					
APS (advanced planning and scheduling)	X	X		X					
MES (manufacturing execution system)	X	X		X				X	X
SCADA (supervisory control and data acquisition)	X	X							
PLC (programmable logic controller)	X	X		X					
HMI (human-machine interface)	X	X							X
DCS (distributed control system)	X	X	X						
Cloud-based storage	X	X							
IIoT (industrial internet of things)	X	X		X					
Edge device	X	X		X					
Data lake/store/base	X	X							
Data historian	X	X		X					
Industrial connectivity (on prem)	X	X							
Digital twin	X	X		X					
Advanced process control	X	X		X					
Manufacturing control tower	X	X		X			X		X
Statistical process control	X	X		X			X		
Augmented reality	X	X		X	X				

D.6.4. Trade-off per digital maturity level

ESRS 1-5

ERP

- **Descriptive:** ERP implementation at this stage often increases energy use. New servers, networks, and data centers add constant electrical demand, while benefits are limited to improved visibility. Without energy-focused features, the digital overhead may outweigh any immediate efficiency gains (Toczé et al., 2022).
- **Diagnostic:** ERP enables identification of inefficiencies, such as excess inventory or idle equipment, supporting targeted energy-saving actions. Even without advanced analytics, diagnostic ERP use can lead to measurable reductions in facility energy consumption (Otis and Hampson, 2017).
- **Predictive:** Forecasting tools within ERP (e.g. for demand, maintenance, or energy pricing) allow operations to adjust proactively. This anticipatory planning helps prevent waste before it occurs and improves energy efficiency (Yurtay, 2025).
- **Prescriptive:** ERP systems at this stage generate optimized schedules and decisions with energy use in mind. Integration with planning and energy tools can reduce consumption by up to 30% through data-driven control (Andrei and Johnsson, 2025).
- **Adaptive:** In adaptive systems, ERP is linked with real-time control (e.g. MES), enabling dynamic adjustments for energy efficiency. This closed-loop approach supports autonomous, energy-aware production (Rogers, 2014).

APS

- **Descriptive:** Energy use typically increases. At this stage, APS is underused, often limited to basic scheduling views or reports. Without optimization, it adds computational overhead without energy benefits. Scheduling still prioritizes throughput or deadlines, not efficiency (PlanetTogether, 2025).

- **Diagnostic:** Energy savings begin as engineers use APS to identify inefficient patterns, such as frequent shutdowns or long changeovers. Diagnostic tools help reduce downtime and waste. In energy-intensive sectors like chemicals, minimizing unnecessary stops delivers clear energy reductions (Ma et al., 2020).
- **Predictive:** APS uses demand forecasts, equipment data, and energy trends to proactively optimize schedules. Predictive planning aligns operations with efficiency targets. Case studies (e.g. GSK) show clear reductions in energy use and emissions through simulation and forecasting (The AnyLogic Company, 2024).
- **Prescriptive:** Modern APS systems include energy as a variable in multi-criteria optimization. Schedules are generated to meet production goals with minimal energy use. Policy sources like the European Commission recognize such tools as essential for industrial energy efficiency (Ma et al., 2020).
- **Adaptive:** APS autonomously adjusts schedules in real time to maximize energy efficiency. The system continuously responds to changing conditions, ensuring optimal energy use at all times. This level achieves the highest possible energy savings through automated, dynamic control (PlanetTogether, 2025).

MES

- **Descriptive:** Energy use may increase slightly. MES improves visibility into operations but does not reduce energy use by itself. If used only for dashboards and reporting, the added energy from servers and IoT infrastructure may not be offset by action, resulting in neutral or slightly negative impact (Langer, 2025).
- **Diagnostic:** Once MES data is analyzed, companies often identify and fix inefficiencies, such as leaks, misused equipment, or poor scheduling, leading to measurable energy savings through targeted corrective actions (Langer, 2025).
- **Predictive:** MES with predictive analytics detects early signs of performance or quality issues, helping reduce scrap and downtime. These improvements translate into lower energy use per unit. Firms like GSK report improved energy efficiency through predictive planning (The AnyLogic Company, 2024).
- **Prescriptive:** MES can actively optimize production flows to avoid energy peaks and reduce idle time. Studies show that integrating MES with energy management and ERP tools can cut energy consumption by up to 30% (Ma et al., 2020).
- **Adaptive:** At this level, MES continuously fine-tunes operations in real time to minimize waste. Advanced users achieve the highest energy efficiency, maintaining predictable, optimized energy use as part of core production control (Langer, 2025).

SCADA

- **Descriptive:** Slight energy reduction. Even at a basic level, SCADA improves energy efficiency by enabling remote monitoring and quicker responses, such as shutting off idle or faulty equipment. The energy used by SCADA infrastructure is minimal compared to the operational benefits (Control Engineering, 2024).
- **Diagnostic:** SCADA data is analyzed to locate and understand sources of energy waste. The system's energy overhead stays constant, but targeted fixes (e.g. maintenance, process adjustments) yield clear savings (Control Engineering, 2024).
- **Predictive:** Integrated analytics allow SCADA to forecast issues and optimize operations proactively. This reduces energy waste by preventing overproduction, avoiding use of backup equipment, and minimizing scrap (van de Scheur, 2025). Net effect: strong energy reduction.
- **Prescriptive:** SCADA works with advanced controls to automatically optimize operations, adjusting setpoints, scheduling loads, or shedding non-critical usage (van de Scheur, 2025). Energy savings are substantial and outweigh the system's own consumption.
- **Adaptive:** SCADA supports real-time, autonomous optimization with minimal additional computing load. The small energy cost of background analytics is outweighed by large, continuous efficiency gains (van de Scheur, 2025).

PLC

- **Descriptive:** Replacing manual or inefficient operations with PLC automation immediately re-

duces energy use. PLCs ensure machines run only when needed and at optimal settings. Their own energy draw is minimal compared to the savings from switching off large equipment when idle (Mochuan Drives, 2023).

- **Diagnostic:** As PLCs help identify and fix inefficiencies, energy savings grow. The control system's low energy consumption remains constant, but improvements in timing, sequencing, and equipment use deliver greater efficiency (Mochuan Drives, 2023).
- **Predictive:** PLCs support predictive logic to shut down or modulate equipment during anticipated idle periods. This prevents unnecessary energy use, deepening net reductions without increasing system overhead (The Veregy Team, 2019).
- **Prescriptive:** At this level, PLCs implement advanced control strategies (e.g. model predictive control) for optimal performance. Reports indicate energy reductions of up to 15% are achievable. The system's minimal energy use is vastly outweighed by the operational gains (Mochuan Drives, 2023).
- **Adaptive:** PLCs help enable fully autonomous, energy-efficient production. Their network draws very little power, and any added algorithmic load is handled elsewhere (e.g. cloud). Net result: maximal energy savings with negligible system cost (Mochuan Drives, 2023).

HMI

- **Descriptive:** This stage may lead to a slight net increase in energy use, as HMI panels (e.g., touchscreens, industrial PCs) consume power continuously. If the interface is only used for passive monitoring, it introduces an energy overhead without generating immediate efficiency gains (Clark, 2025).
- **Diagnostic:** HMIs begin to support energy reduction by visualizing process data and trends. Engineers can use this insight to detect and fix inefficiencies. The small energy cost of running the HMI is easily offset by the savings from informed corrective actions (Clark, 2025).
- **Predictive:** At this level, HMIs provide real-time dashboards, alerts, and forecasts that help proactively reduce energy consumption. Coordinated decision-making using centralized HMI data enables clear energy gains, well beyond the panel's own power use (Clark, 2025).
- **Prescriptive:** HMIs offer actionable guidance and integrate with control systems to minimize idle running and improve process timing. These automated interventions contribute directly to energy efficiency, making the HMI a key tool for reducing consumption (Clark, 2025).
- **Adaptive:** Not applicable. HMIs typically support adaptive systems rather than act as autonomous agents themselves.

DCS

- **Descriptive:** When a DCS is first introduced, it replaces fragmented or manual control systems with centralized automation. This generally leads to immediate energy efficiency gains, as process control becomes more consistent and precise. Although DCS hardware (controllers, servers) does consume electricity, the energy savings from improved plant operation outweigh this overhead. The net result is a clear reduction in energy use (The Confluent Team, 2025).
- **Diagnostic:** As operators begin using DCS data for root-cause analysis and performance tuning, energy waste is identified and addressed more systematically. These insights allow for targeted improvements, and energy efficiency continues to improve. The control system's steady power use remains modest, while its diagnostic value increases energy savings (Worford, 2022).
- **Predictive:** Predictive capabilities are layered onto the DCS, such as forecasting system behavior and proactively adjusting setpoints. The energy required for running these models is minor compared to the large gains from keeping systems in optimal operating windows. At this stage, the net reduction in energy use becomes substantial (The Confluent Team, 2025).
- **Prescriptive:** The DCS begins recommending or autonomously executing energy-efficient actions. Optimization algorithms dynamically tune the process, and control becomes highly responsive to changing conditions. Any computing overhead is negligible compared to the energy savings achieved. The system now operates close to theoretical energy efficiency for the process (The Confluent Team, 2025).
- **Adaptive:** At this maturity, the DCS forms part of an autonomous, self-optimizing loop. Its infrastructure remains low-power by design (embedded systems, efficient networks), while it continuously minimizes energy use based on real-time feedback (Worford, 2022). Net energy reduction

is maximized.

Cloud-based systems

- **Descriptive:** At this stage, cloud usage often results in a net increase in energy consumption. Large volumes of production and sensor data are streamed to off-site servers, consuming network and data center energy. Since the data is mainly used for storage or basic reporting, not for optimization, there are no substantial savings to offset this overhead (Chen and magazine, 2025).
- **Diagnostic:** Energy use in the cloud remains steady, but the value extracted from cloud analytics begins to outweigh it. For example, insights from cloud-based diagnostics might reveal that a heating process can run at lower temperatures, leading to major energy savings in production. This marks the point where cloud shifts from being an overhead to a driver of operational efficiency (Data Dynamics, 2025).
- **Predictive:** Predictive analytics in the cloud, such as forecasting energy demand or optimizing equipment usage, generate significant energy reductions. While running AI and big data models does use cloud resources, modern data centers are highly efficient. The net effect is clearly positive, as the energy saved in the factory far exceeds the cost of computation (Data Dynamics, 2025).
- **Prescriptive:** At this maturity, cloud platforms recommend or directly implement energy-saving actions in real time. The energy used by ongoing cloud computations and data transfer grows slightly, but remains small compared to the energy reductions realized through optimized operations. The net effect is a strong decrease in total energy use (dataPARC, 2025).
- **Adaptive:** Cloud-based systems now operate as part of an autonomous, energy-optimized environment. Their infrastructure is managed for efficiency, while production energy waste is nearly eliminated (dataPARC, 2025). Net energy reduction is at its maximum.

IIoT

- **Descriptive:** In this phase, companies deploy numerous IIoT sensors to monitor variables like temperature, vibration, power, and flow. Each device consumes a small amount of electricity or battery power. Since the data is not yet analyzed or acted upon, the net result is typically a slight increase in energy use due to the additional electronic infrastructure (EPCM Holdings, 2025).
- **Diagnostic:** At this level, while the IIoT device overhead remains, companies begin to leverage the collected data to identify inefficiencies. Quick wins such as eliminating idle energy usage or fixing leaks become common. These fixes usually result in a net energy reduction that outweighs the power draw of the IIoT network (EPCM Holdings, 2025).
- **Predictive:** With predictive analytics, IIoT enables significant energy savings. Advanced monitoring allows for load balancing, predictive maintenance, and process optimization. The overhead for analytics and extra device activity remains minimal, while the energy savings can reach 10–20% in many industrial settings (Emerson Electric Co., 2025c).
- **Prescriptive:** At this stage, IIoT systems deliver real-time, actionable insights to continuously optimize energy usage. The increased communication and processing load from smarter devices is marginal compared to the savings achieved. Overall, the net impact is a strong reduction in energy consumption (Emerson Electric Co., 2025c).
- **Adaptive:** Fully autonomous IIoT networks, paired with AI, continuously refine operations for maximal energy efficiency without human intervention. Studies indicate that such smart factory setups can achieve an additional 5–10% energy improvement beyond prescriptive levels, delivering the highest net energy reduction (Emerson Electric Co., 2025c).

Edge device

- **Descriptive:** In early deployment, edge devices such as IoT gateways or local servers are installed to collect and buffer data from equipment. These devices introduce a small but constant energy overhead. Since they are often provisioned for future workloads, they may initially consume power without delivering energy-saving benefits, resulting in a slight net increase in energy use (Flint, 2024).
- **Diagnostic:** As edge devices begin performing on-site analytics and diagnostics, net energy savings emerge. Because edge computing delivers insights in real time, operational inefficiencies can be corrected quickly. The modest power draw of edge controllers is easily outweighed by the

kilowatts saved through improved equipment behavior and faster issue resolution (Flint, 2024).

- **Predictive:** At this stage, edge devices may perform AI inference or advanced analytics locally. Although this involves some CPU/GPU power use, these devices are designed for efficiency and often reduce their own consumption during idle periods. Meanwhile, predictive optimizations, such as reducing equipment idling or preventing premature failures, yield strong net energy reductions (Informa Markets – Engineering, 2025).
- **Prescriptive:** With continuous, real-time optimization, prescriptive edge intelligence orchestrates equipment performance to minimize energy waste. Studies show edge computing can reduce energy use by up to 70% in specific industrial scenarios by minimizing unnecessary data transfer and enabling low-power local decision-making. The small compute overhead is more than offset by system-wide energy savings (Informa Markets – Engineering, 2025).
- **Adaptive:** Adaptive edge systems use distributed AI to autonomously manage and optimize operations for energy efficiency. While they consume some energy, they are replacing less efficient systems and helping factories operate near optimal energy performance. Case studies show double-digit energy cost reductions, confirming that edge intelligence at this level delivers the highest net energy savings (Flint, 2024).

Data lake & Data historian

- **Descriptive:** At this stage, vast amounts of sensor and operational data are collected and stored, typically in on-premise historians or cloud-based data lakes. However, much of this data is not yet used effectively. The associated storage infrastructure consumes energy for computation, cooling, and networking. As a result, the net impact is negative: electricity is consumed for data accumulation without generating operational savings (Watts, 2024).
- **Diagnostic:** When historical data is analyzed, engineers can identify energy inefficiencies, optimize equipment usage, and avoid recurring waste. Although analytics introduces some compute overhead, the real-world improvements driven by these insights typically outweigh the digital energy costs, leading to a net energy reduction (Watts, 2024).
- **Predictive:** Predictive models built on historical data allow for proactive actions such as predictive maintenance and intelligent scheduling. While training these models may require substantial computing power, the ongoing execution is lightweight and continuously saves energy by improving process timing and reliability. The result is a clear net energy reduction (Watts, 2024).
- **Prescriptive:** At this stage, analytics insights directly feed into decision-making tools or automated control systems. AI-based tools, often working with digital twins or advanced planners, continuously optimize processes for energy efficiency. The IT energy use is minor in comparison to the substantial and sustained savings achieved through optimized plant operations (Watts, 2024).
- **Adaptive:** Adaptive systems use both real-time and historical data to self-optimize continuously. These AI systems adjust strategies dynamically based on changing inputs and can even optimize their own computing energy use. Though distributed learning does require energy, the resulting near-ideal plant performance produces a strong net energy reduction (Watts, 2024).

Industrial connectivity (on prem)

- **Descriptive:** In this initial stage, previously isolated machines are connected through industrial networks or gateways. While this enables data flow, it does not yet impact operations. The networking infrastructure, such as switches, routers, and adapters, adds a small but continuous power load. Since the collected data is not yet used to improve efficiency, the net energy impact is slightly negative due to the added overhead (Genossar, 2024).
- **Diagnostic:** Connectivity now supports system-wide visibility and diagnostics. Engineers can identify and fix energy inefficiencies such as idle equipment, overlapping operations, or poor synchronization. While the power use of the network infrastructure remains steady, operational improvements begin to outweigh the energy overhead, resulting in a net reduction (Genossar, 2024).
- **Predictive:** Connected systems now exchange forecasts and operational status, allowing for proactive energy management. Equipment can adjust in advance to avoid load spikes or idle periods, smoothing energy demand. Since the network's energy cost stays low, the net impact becomes clearly positive as predictive coordination drives substantial energy savings (Genossar, 2024).

- **Prescriptive:** The fully connected factory operates as an integrated system. Intelligent scheduling and control algorithms continuously optimize machine behavior based on energy efficiency goals. The minimal power draw of networking equipment is far outweighed by automated reductions in idle time and energy waste across the operation (Genossar, 2024).
- **Adaptive:** At this level, connectivity enables dynamic reconfiguration of processes in real time. Machines communicate to adjust workloads, speeds, and operating modes based on changing internal or external conditions. Although this results in slightly more data exchange, the additional energy use is negligible, while adaptive optimization ensures sustained energy efficiency (Genossar, 2024).

Digital twin

- **Descriptive:** At this stage, the digital twin is constructed and operated using significant computing resources, such as 3D modeling, physics simulations, and real-time data integration. These systems typically rely on cloud-based HPC or local servers, creating a noticeable IT energy overhead. Since the twin is not yet influencing operations, the net energy impact is negative, with added consumption and no energy savings (Billey and Wuest, 2024).
- **Diagnostic:** The digital twin is now used for simulating operational changes and identifying inefficiencies. Engineers can run what-if scenarios to virtually test improvements, such as sequence changes or speed adjustments, that reveal potential savings of 5–10% in energy-intensive systems. As these recommendations are applied in the real world, the net energy effect becomes slightly positive, with operational savings beginning to outweigh computing demands (Billey and Wuest, 2024).
- **Predictive:** The twin actively forecasts future process conditions and identifies energy waste in advance. Simulations guide preemptive optimizations, with documented cases showing up to 40% energy savings in subsystems like HVAC or thermal processes. Although ongoing simulations increase compute usage, this remains minor compared to the energy conserved in production, resulting in a clear net reduction (Billey and Wuest, 2024).
- **Prescriptive:** The twin now influences or directly controls production processes, continuously adjusting operations for maximum efficiency. Algorithms optimize setpoints, machine paths, and process flows in real time. While compute demands grow modestly, they are vastly outweighed by consistent savings, typically 5–15% or more, achieved through dynamic, algorithmic control. Net energy impact is a strong reduction (Billey and Wuest, 2024).
- **Adaptive:** At this highest stage, the digital twin forms a learning loop with the physical system. AI continuously refines models and discovers new energy-saving strategies based on changing conditions. The system adapts on its own to optimize performance across scenarios. Compute energy use remains modest, while operational energy savings are maximized. The twin functions as a low-power brain enabling continuous, high-impact efficiency (Billey and Wuest, 2024).

Advanced process control

- **Descriptive:** N/A
- **Diagnostic:** N/A
- **Predictive:** N/A
- **Prescriptive:** At this stage, APC scales to multi-unit coordination using a real-time optimizer (RTO) to adjust setpoints across the plant for system-wide energy efficiency. Substantial reductions in steam, electricity, and fuel usage are achievable, often nearing theoretical efficiency limits. Computational demands remain modest and typically periodic. The net effect is a strong energy reduction through holistic, plant-level optimization (Wakasugi and Sueyoshi, 2010).
- **Adaptive:** Adaptive APC continuously maintains optimal conditions by adjusting to real-time changes such as fouling, feed variations, or catalyst degradation. AI-enhanced control strategies and dynamic scheduling integrations further increase energy efficiency. Although compute loads may rise slightly, the system's ability to sustain optimal performance without degradation ensures maximum energy savings (Wakasugi and Sueyoshi, 2010).

Manufacturing control tower

- **Descriptive:** At this stage, the MCT adds infrastructure such as servers, dashboards, and monitoring screens, leading to a small increase in energy use (e.g., 1–2 kW in larger installations). While it

provides visibility into KPIs, it does not yet drive operational changes. As a result, energy savings are minimal, and the net impact is neutral to slightly negative due to IT overhead (Wyciślak and Pourhejazy, 2023).

- **Diagnostic:** The MCT now supports cross-system analysis that reveals inefficiencies such as bottlenecks, excessive scrap, or idle equipment. Addressing these inefficiencies improves throughput and reduces energy per unit. For instance, cutting scrap from 5% to 2% may yield 3% energy savings. As the infrastructure remains unchanged, the net energy effect becomes modestly positive, often in the low single-digit percentage range (Wyciślak and Pourhejazy, 2023).
- **Predictive:** Predictive analytics within the MCT anticipate disruptions such as machine failures or energy spikes. This allows preemptive adjustments to schedules and operations, reducing emergency interventions and smoothing production. As a result, energy usage per output drops. Efficiency gains from demand forecasting and smarter logistics planning lead to a clearly positive net energy impact (Wyciślak and Pourhejazy, 2023).
- **Prescriptive:** The MCT now optimizes production dynamically, deciding when, where, and how to run operations for minimal energy consumption. It may shift loads to off-peak hours, balance production across lines, or reduce peak energy demand. Case studies show energy cost savings of up to 10% through such MCT-driven decision-making. The net impact is a strong energy reduction (Wyciślak and Pourhejazy, 2023).
- **Adaptive:** At this maturity level, the MCT becomes an enterprise-wide orchestrator that integrates factory operations with energy markets and supply chains. It autonomously adjusts schedules in real time to respond to constraints such as outages or price fluctuations and continuously improves via AI. While compute demands (e.g., for model training) may rise slightly, they remain negligible relative to the energy savings achieved (Wyciślak and Pourhejazy, 2023).

Statistical process control

- **Descriptive:** Basic SPC introduces control charts to monitor process stability and catch quality issues early. This reduces scrap and rework, delivering immediate but modest energy savings since each defective unit wastes production energy. Power use is negligible, whether manual or lightly digital. The net energy impact is clearly positive (Avram, 2024).
- **Diagnostic:** SPC data is now used to identify sources of process variation and inefficiency. Reducing variation cuts overprocessing, such as overfilling, excess heating, or cooling, and lowers energy use. Fewer rework cycles and more consistent operations improve efficiency. The system overhead remains minimal (e.g., basic software). Net energy reduction increases (Avram, 2024).
- **Predictive:** SPC becomes a predictive tool, spotting unfavorable trends before process limits are breached. This prevents near-misses, keeps machines efficient, and enables energy-based SPC (e.g., flagging rising power draw due to wear). Compute requirements rise slightly but stay low. Net energy savings become substantial (Avram, 2024).
- **Prescriptive:** At this level, SPC systems recommend or trigger automatic process adjustments in real time, tightening control, reducing downtime, and optimizing energy use. For example, cycle times or heating durations may be adjusted based on trend analysis. When integrated with APC or MES, efficiency further improves. Net energy impact is strongly positive (IIoT World, 2025).
- **Adaptive:** SPC is now embedded in autonomous, self-correcting systems that adjust to raw material variation, environment, or machine wear in real time. Processes stay centered with minimal manual intervention. Scrap, rework, and buffer energy are minimized. The system uses little power, while output remains highly efficient. Net energy reduction is maximized (IIoT World, 2025).

Augmented reality

- **Descriptive:** Initial AR deployment, such as headsets used for digital checklists or basic visual instructions, introduces a minor energy overhead (typically 5–10W per device). At this stage, AR is mostly informational and not yet influencing operations directly. Since energy savings are minimal, the net energy impact is negative, primarily due to device charging and network use (Martindale, 2016).
- **Diagnostic:** AR now supports remote troubleshooting, reducing the need for travel to service machines. For example, avoiding a 100 km service trip saves several liters of fuel. It also improves repair accuracy and speed, cutting machine downtime and idle energy. Net energy impact

becomes positive, as savings from reduced travel, downtime, and scrap begin to outweigh the device energy use (Martindale, 2016).

- **Predictive:** AR integrates with IoT to visualize predictive warnings (e.g., signs of overheating or abnormal energy consumption). Operators receive early alerts and can take preventative actions, reducing failures and unnecessary energy use. Real-time energy overlays guide smarter behavior, such as turning off idle conveyors. The net energy impact becomes significant, as AR-supported decisions cut waste more proactively (Advanced Technology Services, 2025).
- **Prescriptive:** At this stage, AR provides real-time instructions that actively drive energy-efficient actions, such as torque optimization, step-by-step efficient workflows, or reminders to close energy-intensive equipment like furnace doors. The guidance standardizes best practices and reduces human-caused inefficiency. Despite increased AR use, energy draw remains small (Advanced Technology Services, 2025). Net energy reduction is strong.
- **Adaptive:** AR systems become context-aware and adaptive, tailoring instructions to users and real-time conditions. When integrated with AI, control towers, or digital twins, AR helps execute and sustain optimal performance. Improvements are incremental but ongoing. Cloud processing adds minimal overhead (Advanced Technology Services, 2025). Net energy reduction is maximized, as AR fine-tunes and reinforces energy-efficient human-machine interaction.

ESRS 1-6

Since the largest share of greenhouse gas emissions in the Dutch high-tech manufacturing sector comes from electricity use, these emissions are categorized as Scope 2 emissions D.2.2. Based on this, it is assumed that the pattern of GHG emissions follows the same trend as energy use. In other words, if a particular digital manufacturing technology leads to a net decrease in energy consumption at a specific digital maturity level, it is also assumed that this results in a net decrease in GHG emissions at that same level.

ESRS 2-4

DCS

- **Descriptive:** The DCS monitors processes and improves efficiency by reducing off-spec production and unnecessary energy use. While diesel generators may be tested occasionally to ensure DCS reliability, these emissions are minor. Net emissions reduction is likely, as operational efficiency gains outweigh the emissions from support systems (Safdie, 2023; Moss, 2021).
- **Diagnostic:** DCS analytics are used to identify and resolve instabilities early, preventing production faults that would waste fuel or cause emissions spikes. Although genset testing for backup systems may increase slightly, the diagnostic capabilities prevent larger environmental impacts. Net emissions reduction increases (Safdie, 2023; Moss, 2021).
- **Predictive:** The DCS forecasts process disruptions and proactively avoids emergency situations, such as flaring or energy overshoots, by adjusting operations ahead of time. This significantly lowers emissions tied to abnormal operations. Net emissions reduction remains strong, even if system reliability protocols lead to more regular diesel backup testing (Safdie, 2023).
- **Prescriptive:** The DCS now actively optimizes process variables in real time to avoid energy waste and minimize emissions. Setpoints are continually adjusted for maximum efficiency. Any minor emissions from support systems (like UPS or HVAC) are greatly outweighed by process-level gains. Net emissions reduction is substantial (Safdie, 2023).
- **Adaptive:** At this stage, the DCS self-adjusts continuously to maintain optimal operation even under changing conditions. Efficiency is maximized across all scenarios. While testing of backup systems may become more frequent to ensure fail-safe readiness, the overall emissions are significantly reduced thanks to highly adaptive and efficient process control. Net emissions reduction is maximized (Safdie, 2023).

ESRS 5-5

ERP

- **Descriptive:** ERP systems provide visibility into scrap, rework, and material inefficiencies, raising awareness but not yet enabling major interventions. Infrastructure needs are modest, especially if

cloud-based, with minimal environmental footprint. Net impact is a small waste reduction driven by improved monitoring and attention to losses (Gujral, 2024).

- **Diagnostic:** ERP analytics are used to identify the root causes of waste, such as recurring defects or inefficient production planning. These insights support targeted corrective actions that reduce scrap, rework, and excess inventory. While some overhead arises from analytical tools and expertise, the net waste reduction is moderate and measurable (Gujral, 2024).
- **Predictive:** Predictive ERP modules forecast demand, quality issues, or inventory risks, allowing companies to prevent waste before it occurs. This includes avoiding overproduction, spoilage, or excessive procurement. Although computing and storage needs increase slightly, the result is a stronger net waste reduction through proactive management (Gujral, 2024).
- **Prescriptive:** At this stage, ERP actively optimizes planning, procurement, and production through advanced automation. It minimizes waste from errors, expired stock, and inefficient processes, while supporting material reuse strategies. The system's complexity may generate e-waste during upgrades or hardware refresh cycles, but net waste reduction remains strong due to its broad preventive effect (Landman, 2020).
- **Adaptive:** ERP now operates in real time with IoT and MES integration, dynamically reducing waste by rerouting materials, halting flawed operations, or reassigning resources. This enables high circularity and minimizes material losses. However, the extensive digital infrastructure (sensors, edge devices) may contribute to e-waste if not sustainably managed. Net impact: maximum operational waste reduction, with some digital sustainability trade-offs (Landman, 2020).

APS

- **Descriptive:** Basic APS implementation centralizes production and inventory data, helping to expose inefficiencies like overproduction, idle time, or poor demand alignment. Waste reduction at this stage is modest and mainly driven by improved visibility and better planning. IT overhead is low and primarily software-based (HSO, 2025). Net impact is a small but positive waste reduction.
- **Diagnostic:** APS now analyzes schedules to identify root causes of waste, such as frequent changeovers, suboptimal job sequencing, and excess work-in-progress. Scenario modeling enables targeted interventions to reduce inventory waste and scrap. While risks include misoptimization and data quality issues, these diminish with use (HSO, 2025). Net waste reduction increases as scheduling becomes leaner and more efficient.
- **Predictive:** APS uses demand forecasting and disruption prediction to avoid waste before it occurs, by preventing overproduction, missed orders, or rushed rework. Integration with IoT and supply chain data enhances forecasting accuracy, though it also increases digital infrastructure demands. The net effect is a significant waste reduction, partially offset by the environmental footprint of expanding IT systems (HSO, 2025).
- **Prescriptive:** APS now prescribes and dynamically adjusts optimal production schedules to minimize various forms of waste, from excess inventory to inefficient setups and downtime. Industry studies report up to 20% waste reductions from advanced APS tools. Some digital system complexity and minor e-waste appear at this stage, but the overall net impact remains a strong waste reduction (Armstrong, 2024).
- **Adaptive:** APS systems become self-learning, continuously recalibrating in real time based on incoming data. They dynamically prevent emerging waste, prioritize recycled inputs, and avoid risky runs. Operational waste is minimized to its lowest feasible level. However, the complexity of IT systems and density of digital devices may increase e-waste and energy use. Net waste reduction is maximized, if digital sustainability is properly managed (Armstrong, 2024).

MES

- **Descriptive:** MES provides real-time visibility into yields, scrap, and machine status, helping teams respond to issues more quickly. Waste reduction is modest but tangible, mostly through improved awareness and faster interventions. Infrastructure requirements are low, with minimal hardware. Net impact: small but positive waste reduction (Immerman, 2025).
- **Diagnostic:** MES analyzes production data to identify sources of waste, such as specific machines, shifts, or materials. It supports lean practices by reducing downtime, scrap, and rework. While integrating sensors and data systems may slightly increase digital resource use, the process improvements far outweigh this (Immerman, 2025). Net waste reduction increases, driven

by strong operational gains.

- **Predictive:** MES uses analytics and trend data to forecast defects, breakdowns, or energy surges, allowing teams to prevent wasteful incidents before they happen. This reduces material loss and unplanned downtime. Predictive functions require more computation and sensor integration, creating a modest uptick in digital overhead and potential e-waste (Immerman, 2025). Still, the net effect is a significant waste reduction.
- **Prescriptive:** MES systems now take real-time action to prevent waste, such as halting faulty processes, enforcing quality gates, or dynamically adjusting production schedules. This sharply reduces scrap and inefficiency. However, growing reliance on software and hardware, along with periodic upgrades, adds some e-waste (Immerman, 2025). Net impact remains a strong waste reduction, with highly controlled operations.
- **Adaptive:** MES autonomously optimizes production in real time, adjusting processes and schedules to maintain lean, efficient operation under changing conditions. Waste is minimized to its lowest feasible level. The trade-off is increased digital complexity and potential e-waste from dense device networks and IT system evolution (Armstrong, 2024). Net waste reduction is maximized, assuming circular IT practices are followed.

PLC

- **Descriptive:** Basic PLC use automates machines and improves consistency, reducing errors and minor scrap. PLCs flag deviations and enable quicker operator response. The environmental cost is low, with only a slight increase in hardware footprint. Net impact: small but positive waste reduction (Innorobix Automation Inc., 2025).
- **Diagnostic:** PLC data, especially when linked with SCADA, helps identify patterns in waste generation. Engineers can troubleshoot root causes and implement targeted fixes. While legacy PLCs may require upgrades (producing minor e-waste), IT demands remain minimal. Net waste reduction increases through process optimization (Innorobix Automation Inc., 2025).
- **Predictive:** PLCs supply real-time data to IIoT platforms and predictive models that anticipate failures or quality issues. This enables proactive maintenance or parameter tuning, which can reduce scrap by up to 20%. Infrastructure expands to include more sensors and processing power, but the trade-off is worthwhile. Net impact: significant waste reduction with modest digital overhead (Innorobix Automation Inc., 2025).
- **Prescriptive:** PLCs execute automatic corrections to process deviations, ensuring consistent output quality without operator input. Off-spec production and material waste drop sharply. However, supporting advanced logic may require controller upgrades and generate some e-waste. Net waste reduction is strong, powered by real-time closed-loop control (Innorobix Automation Inc., 2025).
- **Adaptive:** PLCs dynamically adjust operations in response to live conditions and AI-driven insights, optimizing performance across varying inputs. This minimizes defects and material waste to near-zero levels. The trade-off is increased hardware complexity, more sensors, edge devices, and AI modules, which can raise e-waste risks. Net impact: maximal waste reduction, assuming sustainable management of digital infrastructure (Armstrong, 2024).

IIoT

- **Descriptive:** IIoT introduces sensors and connectivity to monitor scrap, machine health, and environmental variables. This improves visibility and enables faster response to waste issues. While infrastructure demands are moderate, deploying many devices introduces long-term e-waste risks. Net impact: modest waste reduction, slightly offset by device proliferation (Cinemre, 2025).
- **Diagnostic:** IIoT data is analyzed to uncover waste causes, such as miscalibrated equipment or environmental influences, and support process improvements. These insights reduce scrap and inefficiencies. However, increased reliance on cloud computing adds a minor energy footprint. Net waste reduction increases, driven by data-informed interventions (Cinemre, 2025).
- **Predictive:** IIoT systems support predictive maintenance and quality control by recognizing failure signs early. This prevents avoidable scrap and reduces unplanned downtime. While edge/-cloud infrastructure adds some energy and hardware use, the efficiency gains far outweigh these. Net impact: significant waste reduction with manageable digital overhead (Cinemre, 2025).
- **Prescriptive:** IIoT now automates decision-making, adjusting processes in real time, redirecting

material flows, and enabling circular practices like reintegrating scrap. The growing ecosystem of devices and software increases system maintenance needs (Barresi, 2025). Net waste reduction is strong, but depends on proactive digital sustainability measures.

- **Adaptive:** At this level, IIoT enables fully autonomous systems that dynamically optimize to eliminate waste, compensating for variable conditions or input materials. Near-zero waste is achievable. However, this requires dense, AI-enabled device networks. Net impact: maximum operational waste reduction, assuming lifecycle impacts and e-waste are well-managed (Barresi, 2025).

Edge device

- **Descriptive:** Edge devices provide real-time visibility into scrap, energy usage, and other waste metrics directly on the factory floor. This enables quicker reactions and minor waste reductions. Infrastructure requirements include basic industrial PCs or controllers. Net impact: modest waste reduction, with a manageable hardware footprint (Sustainable Manufacturing Expo, 2025).
- **Diagnostic:** Edge devices analyze live process data to detect defect causes such as misalignment or sensor drift. This allows immediate corrective actions and yield improvement. However, deploying many diagnostic units increases hardware volume. Net waste reduction increases, but e-waste risks rise without proper lifecycle planning (Sustainable Manufacturing Expo, 2025).
- **Predictive:** Edge computing supports predictive maintenance and quality alerts by identifying early warning signs of failure. This prevents scrap and downtime. More advanced edge hardware and AI capabilities are required, increasing the digital footprint (Sustainable Manufacturing Expo, 2025). Net impact: significant waste reduction, though dependent on sustainable device management.
- **Prescriptive:** Edge devices autonomously optimize machines in real time to minimize defects, off-spec production, and idle waste. Localized control reduces material loss and downtime. However, the system becomes more complex and requires regular hardware upgrades (Savill, 2024). Net waste reduction is strong, enabled by continuous edge-driven optimization.
- **Adaptive:** Edge networks learn and optimize entire operations dynamically, rerouting materials, adapting to changing inputs, and reintegrating leftovers. Scrap is minimized, and material circularity is improved. However, the reliance on dense, intelligent electronics makes hardware sustainability critical (Savill, 2024). Net waste reduction is maximized if lifecycle management and modularity are prioritized.

Data lake & historian

- **Descriptive:** Data historians collect time-series information on production and waste (e.g., scrap, rework, resource use), giving engineers visibility into inefficiencies. This awareness enables quicker responses. Infrastructure demands are modest, involving standard servers and software (AVEVA Select California, 2025). Net impact: modest waste reduction, with minimal digital overhead.
- **Diagnostic:** Historical data is analyzed to uncover waste patterns, such as defects linked to specific shifts, materials, or maintenance events. These insights support targeted improvements. Data storage and processing needs increase, but environmental trade-offs remain low (AVEVA Select California, 2025). Net waste reduction grows due to data-driven fixes.
- **Predictive:** Historian data is used to train models that forecast potential waste events (e.g., equipment failure, misalignments). This enables preventive action like timely maintenance or recalibration. Analytics increase digital resource demands, but operational waste savings outweigh the added infrastructure (AVEVA Select California, 2025). Net impact: significant waste reduction.
- **Prescriptive:** Historian-driven simulations and decision-making tools prescribe optimal machine settings, sequences, or maintenance intervals to minimize waste. Integration with other systems adds complexity and hardware refresh cycles (AVEVA Select California, 2025). Net waste reduction is strong, powered by performance-based operational guidance.
- **Adaptive:** Real-time historian data feeds autonomous systems that continuously adjust operations to eliminate waste proactively. This includes predictive maintenance, adaptive process tuning, and scrap reintegration. Requires deep IT/OT integration and regular digital upgrades (Armstrong, 2024). Net waste reduction is maximized, assuming sustainable device and system lifecycle management.

Digital twin

- **Descriptive:** Digital twins visualize real-time process data and material flows, helping identify where waste occurs. This visibility supports early intervention and strategic planning. Infrastructure demands are low, mainly software and light instrumentation (Mügge et al., 2024). Net impact: modest waste reduction with minimal environmental cost.
- **Diagnostic:** The twin is used to simulate scenarios and analyze waste drivers, such as workflow inefficiencies or poor parameter combinations. These insights enable targeted process changes to cut scrap. This stage may require more accurate modeling and additional sensors (Mügge et al., 2024). Net waste reduction increases, with moderate IT expansion and some hardware turnover.
- **Predictive:** Predictive twins simulate future outcomes, allowing proactive changes like speed adjustments or maintenance before waste occurs. This leads to substantial reductions in material losses and defects. Advanced modeling raises computing and energy use, but the operational savings outweigh these. Net impact: strong waste reduction (Mügge et al., 2024).
- **Prescriptive:** The digital twin recommends or directly executes optimal process settings to minimize scrap. Tuning is continuous and data-driven. Integration complexity rises, as do occasional infrastructure upgrades. Net waste reduction is substantial, provided digital lifecycle and upgrade practices are responsibly managed (Mügge et al., 2024).
- **Adaptive:** Operating in a closed loop, the digital twin continuously adjusts processes to prevent waste, even rerouting or reusing scrap automatically. This enables maximum efficiency and circularity. Net waste reduction is maximized, though supported by dense sensor networks, AI, and ongoing hardware updates, highlighting the importance of sustainable IT asset management (Mügge et al., 2024).

APC

- **Descriptive:** Not applicable. APC does not typically operate at this stage.
- **Diagnostic:** Not applicable. APC systems begin to show impact only beyond this stage.
- **Predictive:** Not applicable. The core value of APC emerges at prescriptive and adaptive stages.
- **Prescriptive:** APC automatically adjusts process variables to maintain optimal performance in real time. Defect rates decline due to consistently accurate operation. Net waste reduction is high, with occasional controller or software updates that must be managed sustainably (Applied SmartFactory, 2025).
- **Adaptive:** APC systems self-tune in response to shifts in materials, recipes, or external conditions, maintaining high-quality output without manual input. Scrap and defects are minimized continuously. Net waste reduction is maximal, although reliant on dense digital infrastructure and periodic hardware upgrades, highlighting the need for circular approaches to electronics reuse and recycling (Armstrong, 2024).

MCT

- **Descriptive:** MCT visualizes production and inventory data, increasing visibility into scrap, overproduction, and inefficiencies. Net waste reduction is modest, better awareness enables small improvements. Digital infrastructure introduces a minor energy and hardware footprint (A*STAR Research, 2023).
- **Diagnostic:** MCT analytics identify root causes of waste (e.g., bottlenecks, recurring faults), allowing for targeted interventions. Net waste reduction increases through data-driven fixes. Trade-offs include added computing and moderate IT energy use (A*STAR Research, 2023).
- **Predictive:** MCT forecasts disruptions (e.g., equipment failure, demand fluctuations) to prevent defects, downtime, and overproduction. Net waste reduction becomes significant, with fewer breakdowns and smoother planning. However, the digital footprint grows with expanded sensor networks, AI, and compute infrastructure (A*STAR Research, 2023).
- **Prescriptive:** MCT prescribes or automates decisions (e.g., rescheduling, dynamic material ordering) to enable lean, just-in-time production. Net waste reduction is high, scrap, surplus, and idle time drop significantly. Optimization algorithms increase compute energy needs and system maintenance complexity (A*STAR Research, 2023).
- **Adaptive:** MCT self-optimizes in real time using AI, digital twins, and closed-loop feedback to minimize waste under all conditions. Net waste reduction is maximal. However, intensive ICT infrastructure raises embodied carbon and e-waste risks, requiring circular strategies for device

and system lifecycle management (A*STAR Research, 2023).

SPC

- **Descriptive:** SPC charts visualize process variation and signal deviations, enabling faster manual responses to emerging issues. Early detection helps prevent some defective output. Net waste reduction is minor, with negligible hardware impact, charting may be manual or digital with little to no e-waste footprint (AMREP Mexico, 2025).
- **Diagnostic:** Process data is analyzed to identify and eliminate special-cause variation, stabilizing quality and reducing recurring scrap or rework. Net waste reduction is significant with low digital overhead; the main investment lies in quality engineering effort rather than electronics (AMREP Mexico, 2025).
- **Predictive:** SPC data is used to forecast out-of-control trends, enabling proactive corrections before defects occur. Systems may incorporate sensors and predictive rules. Net waste reduction is substantial. Some added software and sensor infrastructure may be needed but presents minimal e-waste risk (AMREP Mexico, 2025).
- **Prescriptive:** SPC systems recommend or trigger automated adjustments in response to pattern recognition, standardizing corrective actions for consistent quality. Net waste reduction is high, with moderate integration effort. Additional interfaces or modules introduce minimal added electronic load (AMREP Mexico, 2025).
- **Adaptive:** SPC logic is embedded in control loops, enabling self-correcting responses to variation in real time. The system learns from recurring trends. Net waste reduction is maximal. This approach depends on smart sensors and connected controllers, requiring circular planning for hardware upgrades (AMREP Mexico, 2025).

Augmented reality

- **Descriptive:** AR overlays process guidance and visual cues onto physical tasks, helping operators follow procedures correctly and reduce errors. Net waste reduction is modest, enabled by fewer mistakes and rework. Minimal hardware impact from limited AR device use (Rafał Legiędź, 2023).
- **Diagnostic:** AR supports real-time diagnostics by highlighting faulty components or incorrect actions, enabling immediate corrections before defects occur. Net waste reduction is significant through reduced human error. Moderate hardware scaling; recycling plans needed for long-term sustainability (Rafał Legiędź, 2023).
- **Predictive:** AR combines with IoT data to forecast potential process issues or equipment failures, allowing preventive action. Net waste reduction is substantial. Added integration with analytics platforms increases computing and device demands, but benefits outweigh the digital footprint (Rafał Legiędź, 2023).
- **Prescriptive:** AR delivers step-specific instructions and feedback to ensure optimal process execution and error-free outcomes in real time. Net waste reduction is high due to consistent, correct human actions. Hardware and content maintenance requirements grow; e-waste risk manageable with proper lifecycle planning (Rafał Legiędź, 2023).
- **Adaptive:** AR systems learn from user behavior and dynamically adjust guidance to prevent recurring errors, continuously optimizing task performance. Net waste reduction is maximal. Sustained digital precision drives near error-free processes, but ongoing AI and hardware upgrades require circular strategies for device reuse/recycling (Rafał Legiędź, 2023).

ESRS S1-9

AR

- **Descriptive:** Provides visual guidance that reduces physical and cognitive barriers, helping disabled and neurodivergent workers complete tasks independently. Net increase in inclusion, basic overlays and prompts broaden workforce accessibility despite some hardware usability challenges (Tams, 2024).
- **Diagnostic:** Identifies task difficulties and adapts workflows in real time to meet varied accessibility needs (e.g., for visually impaired or cognitively challenged users). Net increase in inclusion, real-time adjustments help more users participate, though tech familiarity can influence ease of use (Tams, 2024).

- **Predictive:** Anticipates user struggles (e.g., from cognitive load) and preemptively offers support like audio prompts or simplified visuals. Net increase in inclusion, proactively enables success for many, despite a slight bias toward tech-native users (Tams, 2024).
- **Prescriptive:** Delivers tailored, real-time instructions that match individual user needs (e.g., voice commands, high-contrast visuals). Net increase in inclusion, personalized guidance removes barriers and brings more people into productive roles, even if some struggle with hardware (Systems, 2024).
- **Adaptive:** Continuously customizes interaction to user ability (vision, mobility, etc.), maximizing autonomy for all workers. Net increase in inclusion, when well-designed, adaptive AR makes nearly all tasks accessible, significantly enhancing workforce diversity (Systems, 2024).

ESRS S1-14

Manufacturing control tower

- **Descriptive:** Monitors machine conditions (e.g. vibration) to flag early warning signs of failure or hazards. Net reduction in accidents, basic visibility improves safety by enabling earlier intervention (IBM Corporation, 2023).
- **Diagnostic:** Analyzes anomalies in machine data to identify root causes of dangerous conditions. Net reduction in accidents, targeted diagnostics lower incident rates, despite increased operator alert fatigue (IBM Corporation, 2023).
- **Predictive:** Forecasts unsafe conditions or failures before they occur, allowing proactive maintenance. Net reduction in accidents, predictive alerts reduce breakdown-related injuries, even if alert fatigue slightly rises (IBM Corporation, 2023).
- **Prescriptive:** Provides real-time maintenance actions or operating limits to keep systems safe. Net reduction in accidents, automated recommendations prevent hazards more effectively than manual decision-making (IBM Corporation, 2023).
- **Adaptive:** Autonomously intervenes (e.g. shut down machinery) to prevent unsafe events in real time. Net reduction in accidents, automated safety responses sharply cut incident rates, even if manual awareness slightly declines (IBM Corporation, 2023).

SPC

- **Descriptive:** Monitors real-time process variation to flag early signs of equipment issues or hazards. Net reduction in accidents, basic charting prompts timely manual intervention before failures occur (IBM Corporation, 2023).
- **Diagnostic:** Identifies abnormal patterns (e.g. out-of-control signals) linked to underlying safety risks. Net reduction in accidents, early diagnostics prevent failures despite minor increases in mental load (IBM Corporation, 2023).
- **Predictive:** Forecasts process deviations (like wear or drift) to allow proactive, safe maintenance. Net reduction in accidents, advanced warnings avert failures, with overall safety outweighing alert-related stress (IBM Corporation, 2023).
- **Prescriptive:** Recommends real-time corrective actions to maintain safe process conditions. Net reduction in accidents, guided interventions reduce hazard exposure, even if rapid response is required (IBM Corporation, 2023).
- **Adaptive:** Autonomously adjusts or halts processes to prevent unsafe operations. Net reduction in accidents, automated corrections minimize risk, with slight trade-off in operator situational awareness (IBM Corporation, 2023).

S1-15

MES

- **Descriptive:** Enables shift data visibility at all times, increasing temptation to check work systems off-hours. Net increase in work intrusion, normalizes after-hours engagement and erodes personal boundaries (Fan et al., 2024).
- **Diagnostic:** Delivers real-time alerts that can trigger urgency outside work hours. Net increase, 24/7 monitoring expectations elevate burnout risks and blur home–work boundaries (Fan et al., 2024).

- **Predictive:** Forecasts disruptions, prompting off-shift planning or reviews. Net increase, constant connectivity pressures workers to stay engaged during personal time (Fan et al., 2024).
- **Prescriptive:** Issues real-time scheduling interventions, often at inconvenient moments. Net increase, frequent alerts reinforce always-available culture, undermining work–life balance (Fan et al., 2024).
- **Adaptive:** Autonomously adjusts operations around the clock, triggering alerts or changes any-time. Net increase, efficiency gains come at the cost of continuous availability, deepening work–life conflict (Fan et al., 2024).

G1-1

- **Descriptive:** Enables incident logging and transparent tracking of operations. When limited to documentation (e.g. safety records), this level supports ethical transparency without targeting individuals. Net effect is potentially positive, transparency improves accountability if not used for performance scrutiny (European Foundation for the Improvement of Living and Working Conditions (Eurofound), 2025).
- **Diagnostic:** Identifies underperformance patterns through analytics. Without governance, this tends to drift into surveillance. Net negative, research warns that diagnostic transparency often shifts toward control unless anchored in ethics training and consent (European Foundation for the Improvement of Living and Working Conditions (Eurofound), 2025).
- **Predictive:** Forecasts individual behavior, such as error likelihood or task delays. This enables profiling and behavioral scoring. Net negative: EU AI guidelines flag such predictive analytics as a risk to autonomy and fairness if unregulated (European Foundation for the Improvement of Living and Working Conditions (Eurofound), 2025).
- **Prescriptive:** Assigns tasks based on algorithmic rules tied to tracked worker data. Reduces room for human discretion in decisions. Net negative: studies show prescriptive systems without contextual input undermine perceived fairness and agency (European Foundation for the Improvement of Living and Working Conditions (Eurofound), 2025).
- **Adaptive:** Automates scheduling and oversight based on real-time behavioral inputs. Monitoring becomes continuous and embedded. Net negative, without explicit transparency rights, adaptive MES creates deep surveillance risks (European Foundation for the Improvement of Living and Working Conditions (Eurofound), 2025).

HMI

- **Descriptive:** Logs basic system interactions such as status acknowledgments, without linking decisions to individuals. When used to report safety risks or support compliance documentation, this aligns with ethical governance practices. Net effect is neutral to positive, transparency without targeted oversight supports ethical use (European Foundation for the Improvement of Living and Working Conditions (Eurofound), 2025).
- **Diagnostic:** Associates specific events (e.g., alarm acknowledgments) with individual operators. This enables traceability of fault and responsibility. Net negative: unless anonymized or governed by clear policies, such tracking introduces surveillance risks and reduces operator trust (European Foundation for the Improvement of Living and Working Conditions (Eurofound), 2025).
- **Predictive:** Uses operator interaction patterns to forecast behavior or risk (e.g., predicting error-prone users). Net negative: profiling workers through predictive HMI use is flagged in the European AI Act as a governance and ethics concern (European Agency for Safety and Health at Work (EU-OSHA), 2023).
- **Prescriptive:** Recommends operator actions and records compliance, including timing and accuracy. This reduces autonomy and increases behavioral monitoring. Net negative, without safeguards like opt-outs or human-in-the-loop review, prescriptive interfaces erode user agency and governance balance (European Agency for Safety and Health at Work (EU-OSHA), 2023).
- **Adaptive:** N/A

Manufacturing control tower

- **Descriptive:** Monitors machine condition and operational parameters without linking data to individual operators. When kept decoupled from user identity, this supports transparent maintenance,

traceability, and system integrity without compromising worker autonomy. Net effect is neutral to positive, supports governance goals if used solely for equipment visibility (European Union Agency for Cybersecurity (ENISA), 2025).

- **Diagnostic:** Associates machine anomalies with specific shifts or operator actions, enabling retrospective fault attribution. Without clear anonymization or ethical controls, this can erode trust and create a surveillance dynamic. Net negative, requires governance safeguards to prevent misuse of diagnostic traceability (European Union Agency for Cybersecurity (ENISA), 2025).
- **Predictive:** Uses historical data to forecast equipment issues and may infer operator-related risk patterns (e.g., associating errors with certain user interactions). This introduces algorithmic profiling risks. Net negative, undermines fairness and inclusion unless tightly regulated under data ethics frameworks (European Union Agency for Cybersecurity (ENISA), 2025).
- **Prescriptive:** Issues real-time operational recommendations based on tracked human-machine interaction data. This can reduce operator discretion and increase perceived behavioral oversight. Net negative, requires transparent communication and opt-in mechanisms to maintain governance balance (Payne, 2018).
- **Adaptive:** Incorporates operator responses into autonomous system adjustments, embedding worker behavior into closed-loop optimization. Without privacy-by-design protocols (e.g., as outlined by ENISA), this results in continuous surveillance (Payne, 2018). Net negative, poses a systemic governance risk unless designed with explicit privacy protections and user agency.

D.6.5. Implementation complexity per digital maturity level

Table D.14: Implementation complexity for each digital manufacturing technology when applied to the ESRS impact at each maturity level.

ESRS	Digital Maturity Level					
	Tech	Descriptive	Diagnostic	Predictive	Prescriptive	Adaptive
E1-5	ERP	Low. Standard feature in most ERP systems, minimal customization.	Medium. Requires tailored data analysis for energy inefficiencies.	High. Requires energy modeling and advanced forecasting tools.	High. Demands integration of energy goals with planning logic.	High. Needs real-time optimization and AI integration, not typical in high-tech ERP setups.
	APS	Low. Dashboards showing energy timelines are easy to implement.	Medium. Requires logic to relate planning inefficiencies to energy waste.	High. Forecasting energy impact of scenarios is not standard and needs modeling.	High. Green scheduling conflicts with high-tech throughput priorities.	High. Real-time autonomous rescheduling to match energy availability is very complex and misaligned with typical continuous production setups.
	MES	Low. MES already supports real-time energy monitoring functions.	Medium. Linking consumption to specific machines/processes needs configuration but is aligned with MES goals.	Medium. Requires modeling energy trends, feasible within MES but needs tuning.	High. Altering schedules based on energy use adds complexity, may disrupt modular production.	High. Real-time, energy-optimized rescheduling is difficult in tightly coupled, high-precision environments.
	SCADA	Low. Basic visibility into energy consumption is SCADA's core functionality.	Low. Root cause analysis of energy issues is well-aligned with standard SCADA usage.	Medium. Alerting on thresholds requires tuning, but no major changes.	Medium. Optimization suggestions demand additional analytics not standard in SCADA.	High. Autonomous control for energy optimization via AI is uncommon and complex in legacy-heavy environments.

EDDC	Digital Maturity Level					
	Tech	Descriptive	Diagnostic	Predictive	Prescriptive	Adaptive
	PLC	Low. Real-time machine-level data is native to PLCs.	Medium. Diagnosing inefficiencies in loops may need custom control logic.	Medium. Predictive alerts require historical data modeling; moderately complex.	High. Implementing model-based control for energy is a significant customization.	High. Real-time autonomous adjustments for sustainability require AI/ML extensions beyond standard PLC capabilities.
	HMI	Low. Energy visibility on machines is easy to visualize.	Low. Basic trend analysis and operator diagnostics fit normal usage.	Medium. Predictive alerts integration with analytics or MES.	Medium. Actionable recommendations require logic extensions or back-end processing.	N/A
	DCS	Low. DCS natively supports real-time process and energy monitoring.	Medium. Diagnosing control loop inefficiencies requires system tuning.	Medium. Forecasting inefficiencies adds modeling layers, moderately complex.	High. Implementing MPC for energy optimization is advanced but feasible in DCS.	High. Autonomous, AI-driven adaptation is complex and not common in existing DCS setups in Dutch high-tech contexts.
	Cloud-based storage	Low. Migration to cloud is increasingly standard; sustainability benefits come passively via infrastructure.	Low. Diagnostics supported natively by centralized visibility across systems.	Medium. Requires aggregation and modeling across multiple sites; added complexity.	High. Integration with real-time optimization across factories is technically feasible but disrupts production flow.	High. Adaptive, cross-site real-time optimization requires high orchestration and is misaligned with high-tech production's stability needs.
	IIoT	Low. Basic machine data capture is standard and aligns with energy visibility goals.	Medium. Diagnosing inefficiencies needs integration with analytics, moderate effort.	Medium. Requires modeling and local processing of trends, supported but not trivial.	High. Real-time actuation based on energy logic introduces conflict with performance goals.	High. Full autonomy with AI optimization at machine level is not common and poses integration challenges.
	Edge device	Low. Simple monitoring aligns with high-tech modular systems and visibility needs.	Medium. Local diagnostics are moderately complex but align with existing needs.	Medium. Predictive modeling adds value but requires development and training.	High. Dynamic machine-level adjustments risk misalignment with rigid quality processes.	High. Autonomous energy optimization is difficult to reconcile with tight process tolerances and interdependencies.
	Data lake	Low. Centralizing data is compatible with existing digital ecosystems.	Medium. Diagnostic insights require configuration and domain-specific knowledge.	Medium. Predictive modeling is well supported but requires ML expertise.	High. Real-time optimization via data lake feedback loops is complex to operationalize.	High. Adaptive streaming optimization is cutting-edge and hard to retrofit in high-precision environments.
	Data historian	Low. Already widely used for historical data storage in high-tech setups.	Low. Diagnostics are standard historian functionality.	Medium. Predictive use cases require external modeling integration.	Medium. Prescriptive insights need optimization logic tied into historian workflows.	High. Adaptive AI optimization based on historian data is advanced and rarely deployed.
	Industrial connectivity (on prem)	Low. Enabling data flow to MES/SCADA is basic and widely implemented.	Medium. Local edge analytics require selective infrastructure upgrade.	Medium. Predictive connectivity support needs edge-cloud coordination and secure channels.	High. Real-time optimization control loops across devices raise integration complexity.	High. Fully autonomous coordination via CPS and AI is highly advanced and rare in practice.

EDEC	Digital Maturity Level					
	Tech	Descriptive	Diagnostic	Predictive	Prescriptive	Adaptive
	Digital twin	Medium. Initial twin modeling requires effort but yields strong energy insights.	Medium. Simulation of inefficiencies fits twin functionality but needs setup.	High. Predictive energy modeling across operational modes is complex and data-intensive.	High. Applying optimized parameters to physical systems must be tightly controlled in high-precision environments.	High. Fully closed-loop twin-to-real-time optimization is cutting-edge and operationally disruptive.
	APC/MPC	N/A	N/A	N/A	High. Optimization for energy efficiency introduces tuning challenges in energy-critical processes.	High. Self-learning MPC for energy is highly sophisticated and requires deep integration with core process controls.
	MCT	Low. Basic visibility into energy KPIs is standard.	Medium. Diagnosing root causes requires multi-source data fusion.	Medium. Forecasting energy-related disruptions adds complexity, but fits well with planning objectives.	High. Action recommendations that alter operations may challenge stability in modular high-tech systems.	High. Real-time autonomous decisioning across the plant floor introduces coordination and trust challenges in precision environments.
	SPC	Low. OEE and defect data already collected; analysis for energy is straightforward.	Medium. Diagnosing energy-linked variance needs correlation modeling.	Medium. Predictive SPC requires integration with energy-related variables.	High. Recommendations influencing machine/process parameters for energy savings can disrupt process performance.	High. Continuous real-time SPC feedback loops for energy are highly sophisticated and not typical in existing setups.
	AR	Low. Visual overlays for energy data are simple and intuitive.	Medium. Diagnostic overlays require backend integration with energy data.	Medium. Predictive simulations demand modeling, moderately complex.	High. Real-time AR guidance must be synced with operations without causing workflow disruptions.	High. Fully adaptive AR systems adjusting workflows based on real-time data are novel and rarely implemented.
	ERP	Low. Tracking production quantities and waste is a standard ERP feature.	Medium. Diagnosing root causes like forecasting errors needs custom analysis logic.	High. Forecasting emissions linked to operations involves complex modeling and integrations.	High. Prescriptive scheduling against emissions requires coordination with business rules and demand fluctuations.	High. Real-time autonomous scheduling for emission reduction not typical in ERP systems, hard to align with rigid high-tech operations.
E1-6	APS	Low. Energy and emission data visibility is achievable with standard dashboards.	Medium. Emission pattern diagnostics require linking external intensity data with planning logic.	High. Forecasting emissions for future schedules requires integration with grid intensity forecasts.	High. Optimizing schedules to align with grid emission patterns conflicts with high-tech throughput needs.	High. Real-time schedule reconfiguration for GHG optimization is extremely complex and operationally risky in high-mix precision environments.

EDDC	Digital Maturity Level					
	Tech	Descriptive	Diagnostic	Predictive	Prescriptive	Adaptive
	MES	Low. Real-time energy visibility aligns with standard MES capabilities.	Medium. Emission diagnostics linked to specific processes need configuration but align well with MES use.	Medium. Predictive scheduling for emission efficiency adds complexity but is feasible with MES extensions.	High. Aligning production with low-emission energy windows may conflict with fixed modular workflows.	High. Real-time energy/emission-aware adjustments pose high risk in environments with long validation/testing cycles.
	SCADA	Low. Real-time fuel/gas monitoring is standard in SCADA systems.	Medium. Diagnosing emissions sources from loops needs specific tuning but is in scope.	Medium. Forecasting emissions from heating/cooling inefficiencies needs modeling, moderately complex.	Medium. Recommending fine-tuned adjustments is technically feasible but requires logic extensions.	High. Autonomous emissions-driven loop tuning is advanced and rarely implemented in legacy-heavy setups.
	PLC	Low. Basic visibility into energy-related control parameters is built-in.	Medium. Diagnosing energy waste from idling or heating inefficiencies requires logic changes.	Medium. Predicting failures and drift affecting emissions adds moderate complexity.	High. Automatically optimizing settings for emissions reduction challenges high-tech process integrity.	High. Real-time adaptive control for GHG minimization is complex and uncommon in current installations.
	HMI	Low. Visual energy/emission insights are easy to integrate.	Medium. Diagnostics on screen require back-end analytics feeding into HMI.	Medium. Predictive insights shown via HMI demand integrations but are feasible.	Medium. Recommending energy-saving actions via interface is straightforward but requires system connectivity.	N/A
	DCS	Low. Energy and emissions monitoring is standard in DCS environments.	Medium. Diagnosing process inefficiencies that cause emissions fits with DCS strengths.	Medium. Predictive control loop drift forecasting is moderately complex.	High. MPC for emission reduction requires advanced configuration and tuning.	High. AI-based autonomous emissions optimization is not common and challenging to validate in safety-critical environments.
	Cloud-based storage	Low. Data centralization aligns with existing IT sustainability efforts.	Low. Emissions-related diagnostics from aggregated data are straightforward.	Medium. Forecasting emissions via predictive models is feasible but adds complexity.	High. Multi-site prescriptive optimization for emissions is difficult to coordinate and validate in real-time.	High. Adaptive multi-site optimization introduces orchestration and security complexities in precision industries.
	IIoT	Low. Real-time energy and machine data is core IIoT functionality.	Medium. Diagnosing emissions-related inefficiencies (HVAC, idle systems) needs smart logic.	Medium. Forecasting emissions spikes based on usage trends is feasible but non-trivial.	High. Automatically adjusting systems in real-time risks conflicting with operational constraints.	High. Fully autonomous GHG-aware operation is advanced and rare in current high-tech deployments.
	Edge device	Low. Monitoring emissions-related parameters is native to edge applications and easily added.	Medium. Diagnostics require integration with control systems but align with localized logic.	Medium. Forecasting emissions trends needs tailored models but is feasible at edge level.	High. Real-time emission-preventive setpoint pushing adds coordination and validation complexity.	High. Autonomous, emission-aware control is advanced and may conflict with tight production constraints in high-tech sectors.

EDEC	Digital Maturity Level					
	Tech	Descriptive	Diagnostic	Predictive	Prescriptive	Adaptive
	Data lake	Low. Centralized data collection fits within existing IT architectures.	Medium. Diagnostic analysis of emissions patterns is achievable with proper tagging and data structuring.	Medium. Predictive emissions modeling is moderately complex but scalable across facilities.	High. Prescriptive optimization across operations demands integrated logic and coordination.	High. Fully autonomous optimization across streams is complex to operationalize and monitor in precision environments.
	Data historian	Low. Historical data collection on energy use is standard in most facilities.	Low. Diagnostic capability is native, with little configuration beyond emissions tagging.	Medium. Forecasting energy inefficiencies for emissions reduction requires external model integration.	Medium. Supporting optimization decisions based on trends fits historian usage but needs extensions.	High. Real-time adaptive control based on historian-fed ML models is sophisticated and rare in practice.
	Industrial connectivity (on prem)	Low. Real-time data visibility is a baseline capability, including energy usage.	Medium. Enabling local diagnostics at the edge adds moderate complexity but fits existing infrastructure.	Medium. Forecasting support via reliable streaming supports scalable predictive modeling.	High. Streaming optimized setpoints to physical processes introduces integration and tuning challenges.	High. Fully autonomous system coordination with AI logic introduces high complexity and trust barriers.
	Digital twin	Medium. Modeling emissions-related inefficiencies adds value but needs detailed process mapping.	Medium. Virtual diagnostics help preempt issues but require strong synchronization.	High. Forecasting energy/emissions outcomes across scenarios requires robust simulations.	High. Virtual-to-real optimization must be validated thoroughly to ensure compliance and process safety.	High. Fully autonomous, adaptive twins are highly advanced and not typical in current high-tech production environments.
	APC/MPC	N/A	N/A	N/A	High. Real-time optimization for emissions reduction requires high-level tuning and stability checks.	High. Self-learning MPC for minimizing Scope 2 emissions is cutting-edge and complex to deploy in regulated, high-stability environments.
	MCT	Low. Emissions-related KPIs can be easily added to dashboard views.	Medium. Diagnosing emissions-related inefficiencies requires correlating across systems.	Medium. Predictive control adds complexity but aligns with existing planning workflows.	High. Prescriptive emission-optimized scheduling can conflict with throughput and cycle time constraints.	High. AI-driven real-time adjustments for emissions optimization require orchestration across many systems and tight integration.
	SPC	Low. Emissions-related insights can be derived from existing quality and process variance data.	Medium. Diagnosing inefficiencies from variability is aligned with SPC's strengths but needs emissions overlays.	Medium. Forecasting drift that leads to waste or overprocessing is moderately complex.	High. Real-time recommendations impacting emissions require integration with process controls.	High. Autonomous SPC adjustments for energy/emissions is rare and complex to validate in quality-critical processes.

EDEC	Digital Maturity Level					
	Tech	Descriptive	Diagnostic	Predictive	Prescriptive	Adaptive
	AR	Low. Visualizing emissions-related data is intuitive and enhances operator awareness.	Medium. Diagnostic overlays require emissions metrics integration but are practical.	Medium. Forecasting inefficiencies in AR tools needs backend model support.	High. AR guidance for emissions reduction must sync with workflow and compliance needs.	High. Autonomous workflow optimization via AR is novel and rarely deployed in structured environments like high-tech manufacturing.
E2-4	DCS	Low. Real-time visibility into process fluctuations is standard in DCS systems.	Medium. Diagnosing emissions-related deviations aligns with core DCS capabilities but needs emissions tagging.	Medium. Forecasting process instability and emissions risks requires trend model integration.	High. Optimizing to prevent venting/burning is advanced and must respect tight tolerances and certification constraints.	High. Autonomous emissions-minimizing process control is technically feasible but complex and rarely deployed in tightly validated production.
	APC	N/A	N/A	N/A	High. Optimization to avoid volatile compound releases requires precise setpoint control and process tuning.	High. Self-learning MPC for emissions stability is advanced and difficult to validate in high-regulation, low-tolerance environments.
	SPC	Low. Monitoring emissions data through SPC is easy to implement using existing infrastructure.	Medium. Diagnosing root causes of emissions requires process linkage but aligns with SPC's diagnostic purpose.	Medium. Forecasting emissions spikes adds complexity but fits predictive SPC frameworks.	High. Real-time adjustment recommendations may affect process parameters, risking deviations from product specs.	High. Fully autonomous emissions-related SPC adjustments are complex and require strong trust in automated quality control under tight tolerances.
E2-5	ERP	Low. Material traceability and usage tracking are core ERP capabilities.	Medium. Diagnosing chemical overuse requires analysis extensions but is feasible.	High. Forecasting hazardous material use across scenarios needs modeling integration.	High. Prescriptive planning for chemical reduction may require coordination with MES and process logic.	High. Dynamic adjustments in real time for hazardous chemical optimization are rare and hard to integrate in precision, regulated environments.
	MES	Low. Visibility into traceability and usage is part of MES foundations.	Medium. Diagnostics for hazardous material misapplications require rule-based tracking.	Medium. Predictive misapplication forecasts align with MES capabilities but need historical modeling.	High. Optimization of hazardous material use in scheduling may interfere with fixed production flows.	High. Dynamic MES-based control for hazardous substances adds operational risk and complexity.
	IIoT	Low. Real-time monitoring of process variables aligns well with IIoT functionality.	Medium. Diagnostics of hazardous deviations require logic at the edge or cloud.	Medium. Predictive alerts about hazardous misuse or process deviation require moderate modeling.	High. Real-time recommendations for quality control may be hard to validate in compliance-heavy sectors.	High. Autonomous control to reduce hazardous scrap is complex and rare in Dutch high-tech settings.

CDC	Digital Maturity Level					
	Tech	Descriptive	Diagnostic	Predictive	Prescriptive	Adaptive
	Edge device	Low. Visibility into key process parameters is easily integrated via edge systems.	Medium. Diagnostics of out-of-spec trends align with standard edge logic.	Medium. Predictive control is feasible but requires tuning per process and material.	High. Real-time corrections related to hazardous substances introduce risk to validated flows.	High. Autonomous quality control for hazardous waste reduction is advanced and not typical in cleanroom or zero-defect contexts.
	Data historian	Low. Capturing process history for hazardous trends is standard.	Low. Diagnosing historical causes of off-spec production fits historian functionality.	Medium. Predictive modeling built on historian data adds moderate complexity.	Medium. Feeding optimization engines for real-time guidance is feasible with configuration.	High. Real-time adaptive correction to prevent hazardous waste is complex and infrequent in use.
	SPC	Low. Monitoring quality metrics related to hazardous production is aligned with SPC goals.	Medium. Diagnostics of deviations affecting hazardous use needs configuration.	Medium. Predictive SPC requires historical quality/emissions links, moderately complex.	High. Prescriptive SPC adjustments can impact core specs, adding validation risk.	High. Fully autonomous SPC for hazardous waste prevention is complex to validate in precision-driven environments.
E5-4	MES	Low. Monitoring material usage is a core MES function and aligns with traceability needs.	Medium. Diagnosing inefficiencies requires linking usage with yield and schedule data, moderately complex.	Medium. Forecasting material needs requires integration with demand and planning systems.	High. Optimizing production to reduce raw material usage must avoid disruption to precision processes.	High. Real-time MES-driven adjustments for material flow challenge high-tech coordination and validation protocols.
	MCT	Low. Real-time resource tracking aligns with MCT's core role in cross-functional visibility.	Medium. Diagnosing resource inefficiencies requires strong data integration across systems.	Medium. Forecasting shortages and inefficiencies is supported but needs custom logic and model tuning.	High. Providing prescriptive recommendations for material reuse or balancing requires careful coordination.	High. Autonomous real-time decisions for workload and material balancing are complex and risky in precision environments.
	AR	Low. Displaying material usage instructions is simple and enhances process clarity.	Medium. Diagnosing overuse in real-time requires feedback loops with MES or quality systems.	Medium. Predicting material inefficiencies through simulations is feasible but non-trivial.	High. Real-time guidance requires accurate backend models and syncing with operator workflows.	High. Fully autonomous AR adaptation of assembly processes is novel and difficult to validate in tightly controlled production.
E5-5	ERP	Low. Visibility into material usage and scrap is standard in ERP systems.	Medium. Diagnosing root causes of scrap requires deeper analytics tied to production processes.	High. Forecasting outcomes for circularity planning needs predictive modeling not typically integrated in ERP.	High. Waste-minimizing production plans require advanced logic and integration with MES/APS.	High. Real-time waste-aware scheduling and optimization is rare in ERP and difficult to execute without production system coordination.

EDDC	Digital Maturity Level					
	Tech	Descriptive	Diagnostic	Predictive	Prescriptive	Adaptive
	APS	Low. Basic tracking of changeovers and material flow is built into APS.	Medium. Diagnosing patterns of inefficiency adds some configuration effort.	High. Predicting off-spec and waste risks in scheduling is complex and not standard.	High. Waste-aware scheduling optimization is hard to balance with throughput and availability in high-tech settings.	High. Real-time rescheduling to reduce waste is very difficult in precision modular manufacturing with long cycles.
	MES	Low. Monitoring scrap, yield, and defect data is native to MES platforms.	Medium. Diagnostics for material waste require linking quality, scheduling, and machine data.	Medium. Predictive scrap forecasting fits with MES extension capabilities.	High. Prescriptive optimization must align with rigid process flows and quality thresholds.	High. Real-time MES-driven optimization for minimal waste requires tight feedback loops and cross-system integration.
	PLC	Low. Task automation for precise dosing and control is standard functionality.	Medium. Diagnostics for mis-dosing and scrap needs tailored control logic.	Medium. Forecasting material overuse and scrap trends is feasible but requires analytics integration.	High. Setpoint optimization for waste reduction must be calibrated to avoid product quality risks.	High. Autonomous material efficiency tuning is highly advanced and rare in existing high-tech PLC environments.
	IIoT	Low. Real-time machine and process data monitoring is a native use case.	Medium. Diagnosing scrap patterns from anomalies fits well with IIoT capabilities.	Medium. Predictive alerts for process deviations are achievable with historical data models.	High. Real-time recommendations must be integrated with MES or control layers, adding complexity.	High. Autonomous, waste-minimizing control is cutting-edge and not common in high-precision contexts.
	Edge device	Low. Visibility into production deviations is aligned with edge device utility.	Medium. Local diagnostics of process issues are supported but must be customized.	Medium. Forecasting faults and inefficiencies at the edge is feasible but non-trivial.	High. Setpoint optimization at the edge requires coordination with broader control systems.	High. Fully autonomous correction for waste reduction is highly sophisticated and uncommon in regulated environments.
	Data historian	Low. Capturing yield, scrap, and process deviations is a core use case.	Low. Diagnostic queries of historical inefficiencies are straightforward.	Medium. Forecasting based on historical waste trends needs model development.	Medium. Prescriptive integration with real-time engines adds complexity.	High. Real-time historian-fed autonomous optimization is advanced and rarely implemented.
	Digital twin	Medium. Visualization of waste risks aligns well with simulation capabilities.	Medium. Diagnostics of defects before they occur fits twin strengths.	High. Predicting scrap under different process scenarios is complex and data-intensive.	High. Prescriptive guidance for reducing waste must be validated before implementation in critical production.	High. Full twin-to-physical autonomous correction is rare and difficult in quality-critical systems.

CDC	Digital Maturity Level					
	Tech	Descriptive	Diagnostic	Predictive	Prescriptive	Adaptive
	APC	N/A	N/A	N/A	High. Real-time tuning to reduce variability and scrap is complex and requires expert calibration.	High. Self-learning MPC for reducing rework and hazardous waste is advanced and uncommon in high-tech facilities due to risk of instability.
	SPC	Low. Monitoring deviation and early identification of waste issues is standard.	Medium. Diagnostics for root causes of scrap or defects fits SPC logic.	Medium. Predictive SPC adds value but requires historical process variation modeling.	High. Real-time prescriptive SPC guidance requires integration with live control systems.	High. Fully autonomous SPC for circularity and waste reduction is rare due to validation challenges in zero-defect environments.
	AR	Low. Visual guidance to reduce assembly errors is simple and valuable.	Medium. Real-time diagnostics require backend process data integration.	Medium. Simulation of scrap-prone processes is feasible with proper modeling.	High. Real-time optimized instructions for waste prevention require syncing with current build status and task logic.	High. Autonomous process adaptation via AR is advanced and rarely adopted in high-spec production setups.
ES1-9	AR	Medium. Visual and interactive guidance is technically feasible, but deploying it in cleanroom or specialized assembly settings may require significant hardware and software adaptation to meet strict operational requirements.	High. Diagnosing task completion issues for employees with disabilities requires integration with input from assistive technologies and user behavior analytics, which are not standard in industrial AR deployments.	High. Predicting employee-specific task execution challenges (e.g., using gaze tracking or behavior prediction) requires custom AI models and personal data integration, which introduces technical and ethical complexity.	High. Adapting instructions in real time to match user accessibility needs (e.g., voice commands, visual adjustments) demands a high degree of personalization and configurability, rarely implemented in manufacturing AR systems today.	High. Fully autonomous and inclusive AR systems that adapt to multiple disability profiles in real-time are highly advanced and require complex system coordination, device compatibility, and ongoing personalization, not common in high-tech industrial contexts.
S1-13	HMI	Low. HMI systems are inherently designed to improve operator usability and reduce cognitive overload. These features directly support inclusion and require no additional configuration for D&I use.	Medium. Highlighting inefficiencies or stress-related operator issues through HMI visualizations may need adjustments to how feedback is displayed, especially to surface D&I-relevant performance gaps.	High. Anticipating inclusion-related risks (e.g., cognitive overload, task misalignment) requires embedding new logic and behavioral thresholds not typical in standard HMI setups.	High. Offering real-time suggestions personalized to operator capability or inclusion needs involves integration with training systems and user profiling, which is outside normal HMI use.	N/A

CDC	Digital Maturity Level					
	Tech	Descriptive	Diagnostic	Predictive	Prescriptive	Adaptive
	Cloud-based	Low. Cloud systems naturally enable remote access and flexible collaboration. These are foundational features that inherently support inclusive working practices without added effort.	Low. Collaborative diagnostics and shared data environments are built into most cloud systems. Using them to support inclusion (e.g., involving diverse teams remotely) is straightforward.	High. Modeling team dynamics or forecasting inclusion-related risks such as exclusion or unequal participation requires new data types and analytics pipelines that are not standard in cloud platforms.	Medium. Recommending inclusion-focused training or collaboration approaches is aligned with cloud's ability to support distributed tooling but still needs tailored logic and integration with HR or learning systems.	High. Real-time, autonomous coordination of inclusion-oriented knowledge flows (e.g., live tailoring of content by role, language, or site) requires complex orchestration across diverse systems and is not typical.
	AR	Low. AR's core features (step-by-step guidance and visual overlays) naturally support multilingual communication and task clarity. This makes it well-suited for inclusive training with minimal adjustment.	Medium. Using AR to detect skill gaps or unsafe task execution involves real-time tracking and feedback, which is achievable but requires calibration for inclusion-focused criteria (e.g., language comprehension, hesitations).	High. Anticipating worker struggles or misinterpretation due to language or background involves predictive modeling of human behavior, which is non-trivial and not native to most AR systems.	Medium. Delivering real-time, tailored instructions based on worker performance or background is moderately complex but aligns with AR's capability when coupled with profiling logic.	High. Fully autonomous, language-sensitive AR that evolves with the user's skill and comprehension in real time demands a high degree of content personalization, AI, and sensor integration. This is complex and uncommon.
S1-14	MCT	Low. MCTs are inherently designed to monitor real-time machine conditions and operational performance. Using this to spot safety hazards is a direct application with no significant adaptation.	Medium. While MCTs can handle integrated data analysis, diagnosing failure patterns for safety-specific root causes (e.g., heat buildup or operator proximity risks) may require adding contextual rules and safety logic.	Medium. Predicting machine failures and unsafe conditions fits well within MCTs' predictive maintenance capabilities, but mapping this to specific health outcomes or regulatory thresholds introduces modest complexity.	Medium. Recommending safety interventions (e.g., equipment adjustment to prevent hazard buildup) is feasible but requires domain-specific knowledge embedded into decision algorithms. This step is moderately complex but achievable.	High. Fully autonomous real-time adjustments for safety go beyond standard MCT usage. This level demands tight coupling with machine control systems, fast decision loops, and compliance integration, especially challenging in high-tech environments.
	SPC	Low. Monitoring machine signals like vibrations to detect early signs of mechanical risk is exactly what SPC is built for. Adapting this for safety insights is direct and low-effort.	Low. SPC's pattern recognition tools are well-suited to flag abnormal process behavior. Applying this to safety-critical indicators (e.g., sudden vibration spikes) fits its core use and requires minimal adaptation.	Medium. Forecasting potential failures tied to safety (rather than just quality) adds a layer of interpretation and modeling beyond traditional SPC. It's a natural extension, but with added calibration needs.	Medium. Making real-time safety-oriented recommendations (e.g., schedule maintenance, adjust tolerances) is feasible but requires translating control chart signals into actionable safety logic.	High. Having SPC autonomously adjust operations (e.g., halt a process when a safety risk is detected) requires tight integration with controls and high trust in automated decisions, rare in current high-tech factory setups.

FDC	Digital Maturity Level					
	Tech	Descriptive	Diagnostic	Predictive	Prescriptive	Adaptive
S1-15	AR	Low. Displaying clear safety instructions and alerts is a natural AR application. Implementing this for complex or high-risk tasks adds value without significant technical burden.	Medium. Diagnosing unsafe behavior by analyzing worker motion or task execution in real time requires motion tracking, context awareness, and safety interpretation, more complex than basic AR usage.	High. Forecasting when a worker might enter a hazardous area or act unsafely needs behavioral modeling, environmental awareness, and advanced analytics, not typically built into AR platforms.	Medium. Delivering real-time, situational safety guidance is a strong fit for AR but still needs workflow integration and customization to the task environment. It's moderately complex, depending on context.	High. AR that autonomously updates safety protocols, provides emotion-sensing, and integrates live environment data represents a cutting-edge, experimental use case. It requires high integration effort and advanced sensing, significantly complex for most factories.
	MES	Low. Basic visibility into workforce hours is a standard MES feature. Highlighting overtime or scheduling issues requires minimal configuration and aligns with core functionalities.	Low. Aggregating and analyzing shift patterns and identifying trends in over-work or irregular shifts is a built-in capability. Very little adaptation needed.	Medium. Forecasting work-life balance risks (like projected overtime) requires modeling workforce patterns in advance, achievable but needs some additional logic and integration.	Medium. Sending alerts or suggesting schedule adjustments based on upcoming overtime thresholds is feasible, but requires active decision logic connected to HR rules or labor policies.	High. Real-time autonomous rescheduling is complex. It demands integration with labor agreements, production planning, and real-time workforce availability, not commonly automated in high-tech MES setups.
	HMI	Medium. Real-time workload visualization for operators is supported in advanced HMI systems but requires integration with sensor data or operational pacing metrics. Not out-of-the-box in most cases.	Medium. Detecting signs of cognitive overload or fatigue in real time is feasible but demands behavioral thresholds and analytics, which go beyond standard HMI setups.	High. Forecasting when a worker may become fatigued or stressed involves advanced modeling of task types, durations, and personal thresholds, requires custom development.	Medium. Providing actionable break or pacing suggestions is possible with sufficient input data but requires deliberate design to avoid productivity disruption.	N/A
	Digital twin	Low. Real-time visibility and remote monitoring are fundamental to digital twin systems and directly support reduced on-site presence.	Low. Remote troubleshooting through simulations is a core capability of digital twins, well-aligned with reducing physical presence and commuting.	Low. Forecasting equipment issues to reduce emergency site visits fits naturally within predictive digital twin frameworks, straightforward to implement.	Low. Suggesting remote optimizations or letting operators make changes without going on-site is a natural and common use of digital twins.	High. Fully autonomous synchronization and adjustment in real time is achievable but demands high maturity in both physical and virtual integration.

CDC	Digital Maturity Level					
	Tech	Descriptive	Diagnostic	Predictive	Prescriptive	Adaptive
	AR	Low. Remote visual assistance and live guidance are standard AR use cases. Requires little customization for maintenance tasks.	Low. Enabling remote diagnostics with expert support via AR is already widely used and aligned with existing capabilities.	Medium. Predicting maintenance needs and deploying remote solutions requires data integration from systems that track wear/failure.	Low. Delivering step-by-step instructions through AR overlays is common and low in complexity for trained technicians.	High. Real-time autonomous adjustment of AR content based on maintenance conditions, while enabling fully remote repairs, demands advanced sensing, personalization, and environment understanding.
G1-1	MES	Low. Logging safety incidents and near-misses from the shop floor is a standard MES feature. It directly supports transparency and accountability with minimal integration effort.	Low. Analyzing incident reports to find recurring issues is a core MES use case. Aligning this to ethics (e.g., ensuring response to repeated issues) requires no significant system adaptation.	Medium. Using historical data to forecast safety risks adds moderate complexity. Ethical alignment (e.g., acting before harm occurs) is conceptually simple but may need additional risk models.	Medium. Recommending ethical safety improvements based on incident analysis is feasible but requires customized logic to prioritize responses based on severity, responsibility, or harm potential.	High. Automatically halting production in response to real-time incidents is a powerful ethical safeguard, but it requires tight process control integration, confidence in real-time triggers, and override handling, complex to implement without productivity risks.
	HMI	Low. Enabling operators to report safety issues in real-time is a basic function of HMI systems and strongly supports ethical transparency with minimal additional implementation.	Low. Analyzing reported issues to prioritize corrective actions is aligned with standard HMI data handling. Mapping these priorities to ethical goals (e.g., fixing high-risk issues first) is straightforward.	Medium. Forecasting future risks by analyzing trends requires more advanced data interpretation and modeling, feasible, but more complex than direct reporting or diagnostics.	Medium. Recommending corrective actions based on past reports is achievable, but it requires integrating rule-based or logic-driven decision models to align with ethical goals.	N/A
	MCT	Low. Providing full production visibility to stakeholders is a core function of MCTs. It directly supports ethical practices and requires no adaptation for this purpose.	Low. Tracking causes of issues and enabling traceability through data aligns perfectly with MCT functionality. It naturally supports data-driven accountability and ethical oversight.	Medium. Anticipating ethical risks (e.g., waste, supply shortages) and acting in advance supports responsible behavior. This requires moderate modeling and interpretation.	Medium. Making recommendations to align operations with ethical standards (e.g., waste reduction, safe operating procedures) is conceptually feasible, but complex to standardize across departments or decisions.	High. Fully autonomous adjustment of operations to align with ethical standards is highly advanced. It demands real-time integration, compliance alignment, and decision autonomy, complex in high-tech environments with strict tolerances.

Phase 4 materials

E.1. Supervised survey interviews

E.1.1. Interview protocol

Begin with an introduction of myself and the research. Explain that the goal is to evaluate a decision-support tool designed to support the implementation of the Twin Transition (digitalization and sustainability) in Dutch high-tech manufacturing companies. Emphasize that the interviewee's feedback will help assess the tool's relevance and effectiveness. Ask if the interviewee has any questions about the consent form. Repeat the consent elements previously shown to the interviewee during the before provided and signed consent form. Ask for a brief introduction of the interviewee. Verify the name and current role of the interviewee.

1. Starting questions

These initial questions aim to provide context and gather the interviewee's background:

1. *Can you briefly describe your role and experience in/with the Dutch high-tech manufacturing sector?*
2. *Have you been involved in digital or sustainability-related initiatives in your work? If so, could you give a brief example?*

2. Tool walkthrough and interaction

(The walkthrough and interaction were adapted depending on whether the survey was completed in advance or during the interview.)

- The researcher shares their screen and demonstrates the web-based decision-support tool.
- If the participant did not fill in the survey beforehand:
 - Demonstrate the survey interface (opening screen, dimension selection, ESRS impact prioritization).
- For all participants:
 - Show the maturity assessment overview and detailed breakdown.
 - Demonstrate how recommendations are generated for each selected ESRS impact.
 - Explain the implementation complexity and trade-offs across dimensions.
 - Tailor the walkthrough to the participant's expertise (use familiar technologies to validate framing; unfamiliar ones to test clarity).

Open discussion questions during the walkthrough:

- *What is your first impression of the decision-support tool?*
- *Does this feel like a tool you could use in your work? Why or why not?*
- *How would you envision using this tool in a real-world scenario?*

3. Supervised survey and requirement evaluation

(Use split-screen to display the tool on one side and requirement list on the other.)

- Explain: "In an earlier stage of this research, a set of requirements was developed for this decision-support tool. I'd like to assess with you whether you believe the tool fulfills these."

- Guide the participant through each requirement and ask them to rate it:
 - Not fulfilled
 - Partially fulfilled
 - Fully fulfilled
- Follow-up prompts for each requirement if suitable:
 - Why do you think that?
 - How important is this in your experience?
 - Can you give an example from your work where this would apply?

4. Closing questions

1. *Is there anything you feel is missing in the tool?*
2. *What would make the tool easier to use or more useful for you?*
3. *Is there anything else you'd like to add that we haven't discussed yet?*

E.1.2. Interview summaries

Interviewee C1

Overall impression C1 described the tool as a promising framework to help companies explore how digital technologies can advance sustainability goals. Its strength lies in guiding users through trade-offs between sustainability gains and potential drawbacks like increased energy consumption. According to C1, "If you can clearly present the benefits purely from a sustainability perspective in one tool, then that really does have value."

While the foundational structure was considered sound, C1 saw the tool primarily as a starting point for discussion rather than a finalized decision-making instrument. "The numbers will never be 100% accurate, but what matters is that it triggers the realization: 'oh yes, there is something we can work with.'"

Usability: clarity and customization

C1 appreciated the interface and logic behind the maturity assessment, calling it "clearly laid out," and confirmed that the tool allows companies to express their specific sustainability priorities. According to C1, the tool enables customization across ESG dimensions and supports users at varying digital maturity levels. "I do think it meets that need, yes. That's definitely in there."

However, C1 noted the importance of explicitly differentiating between the maturity levels of different technologies. The scoring was found to be too uniform in some cases, which undermines the granularity of recommendations. "Now I mostly see just a sample... but if there are many of those, then it's definitely valuable."

Validity: room for technical correction

A key point of critique was the technical accuracy of the tool's literature-based assumptions. C1 disagreed with how certain systems were represented in the recommendations, especially ERP systems being credited with capabilities such as real-time production monitoring. "ERP does not do real-time monitoring of production processes."

Similarly, literature-based assumptions about sensor deployment were challenged. C1 explained that many sensors are already embedded in machinery and that large-scale sensor deployment is not typical at the start of digitalization. "It's almost never the case that sensors are purchased separately. It can happen, but yes..."

Usefulness: high-level orientation, limited depth

C1 acknowledged that the tool clearly presents sustainability trade-offs, particularly in how technologies may consume resources while enabling efficiency gains. "I do see clear trade-offs... you incur costs from an environmental perspective, but you also have benefits." They confirmed that for material use and waste, digital technologies almost always resulted in net benefits. While C1 recognized the tool's value in generating awareness and direction, they were clear about its current limitations for in-depth implementation planning. "You would actually want a more in-depth text than this... What exactly does a digital twin do?" They suggested more extensive descriptions of each technology, explaining both its function and expected sustainability impact. Without this, the tool's outputs risk being too vague for operational use. "For example, what can you actually do with a control tower?"

Toward practical application

Despite its early-stage nature, C1 saw clear potential for applying the tool in consulting scenarios, if further developed. For instance, in conversations with clients about digital sustainability strategies, it could help anchor the discussion in data and structure. "I can definitely see that... if you move from here to there, then you have those benefits. That definitely has value, yes." They stressed the need for contextual depth and more nuanced comparisons between technologies to make the tool actionable in real-world settings.

Conclusion

C1's assessment of the decision-support tool was both constructive and critical. While recognizing its clear structure, customization options, and conceptual value, they emphasized that it remains an early-stage instrument. Enhancements in content specificity, technical accuracy, and practical detail would be required for the tool to serve as a standalone guide or client-facing solution. As C1 summarized: "The concept is good... but it still needs to be worked out with more in-depth implementation."

Interviewee C2 & C3**Overall impression & usefulness**

A significant positive impression of the tool stems from its ability to raise awareness and help in prioritizing initiatives. C2 noted that filling out the survey, already made them realize gaps in their current data collection and sustainability efforts. "At such a moment, I thought: 'Oh yes, we don't actually have this yet.' Then you realize: if we find this important, we need to start working on it. That awareness helps tremendously."

The interviewees believe the tool's output, particularly a "maturity measurement" report, would be highly valued by the management board, especially the CTO. C2: "C3, if you go to the management board with this (for example, to the CTO) they would really like to see these kinds of insights." They believe the tool could be used to discuss the difference in progress between different manufacturing sites and could highlight where the gaps and possibilities are. The tool could help them "become aware that technology can really help us" according to C2. C3 added that the tool can be an interesting conversation facilitator, since it provides a common framework for manufacturing and sustainability to discuss sustainability: "If you have conversations without such a framework, you speak different languages so to say. This creates common ground."

The tool's comprehensive approach, integrating Environmental, Social, and Governance (ESG) aspects, was also well-received. C3 appreciated that the tool considers these different dimensions, allowing for a more holistic view of trade-offs. "Yes, that's right. You've included ESG, so you're not just looking at one component. This also shows the trade-offs. That works well."

Furthermore, the interviewee recognized the tool's potential to support organizations at different maturity levels. C2 stated, "Yes, if I look at the questions, there is indeed a nice spread." The ability of the tool to make trade-offs insightful was also acknowledged. C3 noted, "Yes, that confirms what you intuitively suspect."

Real-life application limitations on the use of the tool

Varying digital maturity and data availability across factories was a recurring and prominent theme. The interviewees emphasized the significant differences in digital infrastructure and data collection capabilities across their multiple locations.

C2 provided a stark example: "We have a similar machine in [Country A], but it doesn't have new PLCs. So you can't get that data out of it. Then you can only look at the level of the entire department. And then you still have machines from 1965..." This directly contrasts with newer facilities like the one in [Country B], where they can "just monitor live" data from new machines. This disparity means the tool's data-driven insights would be far more granular and actionable in some locations than others.

The need for "master data to be in order" was strongly emphasized by C2: "What I have seen in my experience... is that your basic data must be correct. Only then can you report reliably. And only if that basis is correct, then you can improve." This implies that even with a willingness to use the tool, fragmented or unreliable data sources would severely limit its effectiveness. C2 described their company as "a conglomerate", with entities growing together over 20 years. Only recently did all operational locations agree to report jointly. This inherent structural complexity means that standardization across systems, which C3 noted as "Important. Then you can make much faster steps," is a significant ongoing

challenge.

Validation of technology recommendations

The interviewer specifically brought up Augmented Reality due to the company's significant assembly operations. The interviewee's feedback on AR was mixed, acknowledging its potential while also pointing out limitations for their specific environment. C2 directly stated a successful pilot experience with AR for training: "We have for example at [a sub-division] done a pilot with augmented reality. But some operators said: 'it slows me down.' Ultimately, we agreed that it works better for training people, to make them aware of certain actions." The interviewer suggested AR could assist people with physical or sensory limitations. C3 acknowledged this as an "interesting direction to think about for the future," particularly in the context of labor shortages, even if their current production process isn't immediately suitable. This shows an openness to AR's social sustainability benefits. C2 recognized that AR could be beneficial in "assembly areas where less repetitive actions take place."

The interviewees generally agreed that MES systems, by providing more detailed operational data, enable more targeted improvements in energy consumption and waste reduction. C2 noted that by understanding machine-level data, they can "increasingly look in a more targeted way" and "step by step get closer to your sustainability goals." However, C2 noted that in [a country], where a new MES system was being introduced, "employees find the real-time tracking part quite stressful," which was directly in line with the trade-off made by the tool.

Financial considerations

C2 directly highlighted the substantial investment costs associated with certain digital technologies, while questioning their demonstrable return on investment for sustainability. For example, regarding a SCADA implementation, they stated: "Nice systems, but a SCADA implementation costs about five hundred thousand. We get data and some tools in return, but I wonder: does it demonstrably yield anything for energy or sustainability?" This indicates a desire for clearer financial justification for these investments, which the tool currently struggles to provide due to the inherent complexities.

Due to variability in manufacturing companies and their specifications, the interviewer concluded that the tool would primarily offer qualitative guidelines rather than specific financial figures, as it was not possible to estimate a sensible range of investment. The interviewer suggested that the business case should be calculated case-by-case. C2 responded with "Recognizable. Really very recognizable," indicating their understanding and agreement with this limitation.

Suggestions for improvement

C2 pointed out that the survey, while detailed, assumed a level of data availability that isn't always present in practice. They said, "What I noticed when filling the survey in, is that the minimum you could check sometimes already seemed too much, I don't mean that negatively. But it felt as if it was assumed that we already have all the data available. And that's sometimes just not the case." This highlights a challenge in the tool's applicability to organizations with less mature data infrastructure. They suggested a valuable improvement: "There maybe should be an option zero as well. Then you also more clearly identify the gaps, what is still missing." According to the interviewees, the zero-maturity should then not be excluded from the maturity overview, but should be highlighted in a separate section, to put focus on what is still missing. A clear report highlighting areas where the company has no current initiatives or data would transform a potential negative (lack of data) into a clear call to action.

Another area of concern are the benchmarking capabilities of the tool. While the idea of benchmarking is appealing, C2 questioned the practicality without comparable data. "That seems very interesting to me. The question is: against whom do you benchmark then? You want to be able to compare yourself, but with a comparable company." C3 echoed this, noting the difficulty of finding truly comparable benchmarks, often resorting to comparing CO₂ emissions relative to company size, which can be misleading. "But sometimes that's misleading, especially if you only compare a small part of the production process." This suggests that while the tool can quantify maturity and enable self-benchmarking over time, its external benchmarking validity is currently limited by data availability outside the tool itself.

While the tool already quantifies maturity levels, making this aspect more prominent and perhaps visually engaging in the output report would appeal directly to the technical staff. C2 explicitly stated, "Many of our technicians would really like that, a kind of maturity measurement: 'Oh, look, this is how far we've come.'" The interviewees both envision deeper explanations of the maturity scores and integrating

that in the visuals as well. As C3 put it: "When you see a '2,' what does that really mean?"

Interviewee C4

Overall impression & usefulness

C4 expressed a very positive overall impression of the decision-support tool, particularly emphasizing its clarity, structure, and potential to facilitate strategic conversations. "I found the survey clear and pleasant to fill out," they stated. The survey format was described as intuitive, especially after answering a few questions: "After three or four questions, I really got into a flow."

C4 praised the tool as a strong conversation starter with real value: "What you've developed here is an initial inventory. The starting point for the conversation." they even noted they could "think of ten clients right away" who would benefit from using it. They see it being used to "create urgency" by visually highlighting where a company stands and where its biggest gaps lie. According to C4, the tool serves as a "stepping stone" that helps identify priorities and frame discussions with stakeholders like plant managers or corporate leadership.

Completeness & structure of the survey and connection to the dashboard

C4 complimented the survey's content, stating, "I understood it well and found the questions relevant. I filled everything in because I found it interesting, so that's really a compliment." However, while they understood the survey, they suggested more visuals: "It came across to me as a decision tree, but in a lot of text... The content is good, but the presentation could be more visual." They suggested adding more visuals or graphical elements to help the user "see where they or she is in the process."

While they appreciated the dashboard's visual clarity, C4 strongly felt the absence of a "one-pager" summary after completing the survey. "What I missed most was really that one-pager. Afterwards, I noticed: okay, I filled everything in, but what now? What are the conclusions? What is my starting point?" they emphasized the need for an immediate "overview of the outcome" after investing time in the survey, instead of seeing the web-application at a later stage.

C4 generally estimated the industry's maturity as "quite low," concurring that "the industry is still lagging." They noted that advanced questions (level 2 or higher) often address things that are "theoretically good" but "hardly anyone really gets around to now." For instance, with AI and generative AI, most customers don't even have their data in order yet, let alone that they are doing anything with AI according to C4.

However, C4 highlighted a potential issue with the survey: "someone could very easily give socially desirable answers." They noted that companies "want to present themselves positively on sustainability", which is something that could be addressed in the survey. Also, C4 strongly agreed with the idea of adding a "level zero" to the maturity assessment, as some companies are "still below level 1." This would help to "more clearly identify the gaps, what is still missing."

Recommendations of technologies

C4 found the implementation complexity aspect "a bit more superficial," desiring more depth beyond just an indicative score. They suggested adding a kind of explanation when hovering over each technology, clarifying why it's difficult (e.g., SPC is difficult to implement because you need high-quality data and algorithms at a certain level). This would help users understand what technology implementation actually entails. C4 emphasized this, as terms like control tower can be interpreted differently by different stakeholders: "[A client] has a different image of what a control tower is than I do. Not better or worse, just different."

Limitations of the tool

C4 confirmed that the peer-benchmarking feature was "not present" in the tool. they acknowledged it's "a very difficult" task, agreeing that it would only be feasible once "multiple companies have completed the survey." They emphasized the difficulty of comparing factories due to "technical differences" and varying production processes, calling it a "consultancy hobby, but rarely truly meaningful," though managers often request it.

C4 furthermore acknowledged the difficulty of providing a quantifiable ROI, stating, "ROI is not simple in this industry. It's not as direct as in other sectors." they explained that "everything is connected to everything." they highlighted the non-technical challenges of implementation, such as convincing various stakeholders (e.g., "VP Production, the VP Quality, the plant managers") which can take "months."

they felt that quantifying a benefit or ROI is "very difficult" and that this kind of project is best suited for "time & material" contracts, not "fixed price."

Specific technology insights & tool validation

- APS: C4 found APS interesting because it highlights the dilemma of planning for energy consumption versus production efficiency, where "you might produce less efficiently, and thus lose profit." They agreed that if used explicitly for sustainability, it would be "medium" or "high" in complexity.
- Edge devices: they agreed that if implemented correctly, edge devices lead to a "net reduction in energy consumption," even with their own energy usage, confirming the tool's trade-off insight: "it is clearly worth it. I see that too."
- Augmented reality: C4 shared a compelling example of AR for health & safety in a factory using infrared sensors to show hot pipes, preventing burns. They affirmed its value but noted its difficulty and cost: "those kinds of technologies are valuable, but difficult to implement. It's expensive and requires a lot of preparation."
- Control tower: C4 called the control tower "the most important goal of any digitalization effort." They agreed it enables predictive maintenance and, crucially, allows for the identification and sharing of "best practices" across factories, thereby improving safety and implementing standards. However, they also highlighted significant non-technical challenges, especially in companies formed through acquisitions. They noted "a kind of power struggle between corporate and the factories" where data sharing is sensitive if it exposes "weak points" like low OEE.
- SPC: C4 aligned with the tool's assessment that SPC requires "a lot of data, and more importantly: that data must be of good quality." They stated that many of their clients are "far from ready for SPC" because they lack the right basis and are not truly data driven.

Suggestions for improvement

- Aspirational vs. foundational technologies: C4 strongly suggested adding an indication (next to the implementation complexity) in the tool for which digital manufacturing technologies are "aspirational" and what is "foundational." They believe a control tower should be foundational but often is not in practice due to obstacles, while SPC is "truly aspirational." This nuance would make the tool more "applicable in realistic situations."
- Process complexity differentiation: C4 stressed that the tool must better account for sector and process complexity. Some factories with more straightforward manufacturing processes require minimal digital innovation, while others may benefit greatly. "Maybe your tool should first ask: 'What is even needed here?'"
- Report-out clarity and urgency: C4 emphasized the importance of the tool's "report-out" to "lay a good foundation for what comes next." they advised making it "immediately clear visually" where the biggest gap is (e.g., "you have done too little in the area of environmental"), as this "creates urgency." This could be highlighted both visually and textually in the first overview, emphasizing the gap between current and target maturity.

Interviewee C5

Overall impression & usefulness

C5 responded positively to the decision-support tool, recognizing it as a high-level awareness and orientation tool. They appreciated that it helps companies understand how digital technologies can support sustainability goals: "The tool can start the discussion." C5 emphasized that such a tool is most valuable in the early stages of strategic reflection.

Perceived completeness and validity

C5 confirmed that the tool "fulfilled" its purpose of integrating company-specific priorities through the survey component, where users select which ESG topics matter most to them. However, the quantification of maturity stages was seen as "partially fulfilled," as C5 questioned how measurable the scores really are: "You do provide a rating, right? But how quantifiable that rating really is, I'm not entirely sure." Similarly, while the tool visualizes sustainability trade-offs, C5 pointed out that the analysis is necessarily generic and can only serve as a starting point: "Trade-off analysis is quite complex and very company-specific."

Maturity assessment and benchmarking

The tool's functionality for self-benchmarking, tracking a company's own progress over time, was rated positively: "Yes, that works." However, C5 noted the absence of peer benchmarking and highlighted its importance: "Companies are always interested in how they compare to their peers." They encouraged future development in this direction, suggesting that collecting data over time could motivate broader participation: "That kind of feedback loop would motivate companies to take part, and to share their data in the first place."

Assessment of features and trade-offs

- Implementation complexity: C5 saw value in the complexity rating of technologies but suggested adding contextual explanations: "I would be interested in that as a company, or maybe you could include a link to more details."
- Trade-offs within ESG: They acknowledged the tool's value in highlighting trade-offs but stressed its limits: "A tool can only ever support the first step in that process."
- Cost-benefit assessment: This feature was noted as missing: "No, not really." C5 found the decision to leave it out understandable given the variability across companies.

Suggestions for improvement C5 recommended:

- Including justifications or short explanations alongside complexity ratings.
- Building in benchmarking capabilities based on aggregated peer data over time.
- Using feedback loops to incentivize company participation and data sharing.

Envisioned use case

C5 sees the tool primarily as a "first-step conversation starter" that enables companies to reflect on how digital solutions intersect with their sustainability efforts. Its main function would be to raise internal awareness, guide strategic discussions, and highlight which areas warrant deeper, case-specific analysis.

E.2. Application of the 5E framework per interviewee

Table E.1: Interviewee assessment of the decision-support tool across the 5E framework dimensions.

Dimension	C1	C2 & C3	C4	C5
Efficacy	C1 believes the prototype already surfaces valuable sustainability insights and sparks "realization," so the core purpose is met in principle. According to C1: "If you can clearly present the benefits purely from a sustainability perspective in one tool, then that really does have value."	The participants saw strong potential for awareness-raising, with C2 noting: "At such a moment, I thought: 'Oh yes, we don't actually have this yet.' Then you realize: if we find this important, we need to start working on it. That awareness helps tremendously." They believed the tool could help them "become aware that technology can really help us."	C4 expressed very positive views on the tool's core purpose, stating: "What you've developed here is an initial inventory. The starting point for the conversation." They could "think of ten clients right away" who would benefit and saw it as effective for creating "urgency" by highlighting gaps.	C5 recognized the tool's value as a high-level orientation tool, stating: "The tool can start the discussion" and saw it as valuable in the early stages of strategic reflection.

Dimension	C1	C2 & C3	C4	C5
Efficiency	Because the survey lets users focus only on topics that matter to them, C1 sees the workflow as time-well-spent. No remarks about excessive effort or cost were made. According to C1: "I do think it meets that need, yes. That's definitely in there." on being able to tailor priorities.	They appreciated the comprehensive ESG approach, with C3 stating: "You've included ESG, so you're not just looking at one component. This also shows the trade-offs. That works well." However, they noted the survey assumed data availability that isn't always present: "it felt as if it was assumed that we already have all the data available. And that's sometimes just not the case."	The survey was praised for its flow: "After three or four questions, I really got into a flow" and "I found the survey clear and pleasant to fill out." However, they noted the need for more visual elements: "It came across to me as a decision tree, but in a lot of text."	They appreciated the integration of company-specific priorities through the ESG selection process, confirming the tool "fulfilled" this purpose.
Effectiveness	C1 acknowledged real-world applicability challenges, viewing it as "a starting point for discussion rather than a finalized decision-making instrument." They emphasized: "The numbers will never be 100% accurate, but what matters is that it triggers the realization: 'oh yes, there is something we can work with.'"	Real-world application faced significant challenges due to varying digital maturity across facilities. C2 explained: "We have a similar machine in [Country A], but it doesn't have new PLCs. So you can't get that data out of it... And then you still have machines from 1965..." They emphasized: "your basic data must be correct. Only then can you report reliably."	C4 acknowledged real-world complexity, noting that "ROI is not simple in this industry" and that "everything is connected to everything." They emphasized non-technical implementation challenges, such as convincing stakeholders, which can take "months."	C5 questioned the measurability of outcomes: "You do provide a rating, right? But how quantifiable that rating really is, I'm not entirely sure." They noted that "Trade-off analysis is quite complex and very company-specific," limiting real-world application.
Elegance	C1 appreciated the clear structure, calling the interface "clearly laid out" and confirming the tool "allows companies to express their specific sustainability priorities."	They appreciate the holistic ESG view and find the outputs readable, but offered no detailed comments on visual or interactive polish: "Yes, that confirms what you intuitively suspect."	While appreciating the content, C4 wanted more visual presentation and missed having "that one-pager" summary after completing the survey: "What I missed most was really that one-pager. Afterwards, I noticed: okay, I filled everything in, but what now?"	C5 found the self-benchmarking functionality worked well ("Yes, that works") but noted the absence of peer benchmarking as a limitation.
Ethicality	C1 voiced no concerns or praise regarding fairness, inclusiveness, or transparency.	The tool's consideration of social aspects was appreciated, particularly regarding AR's potential to assist people with limitations, which C3 called an "interesting direction to think about for the future."	C4 raised concerns about potential for "socially desirable answers" since companies "want to present themselves positively on sustainability," suggesting a need to address response bias.	Not addressed by C5.