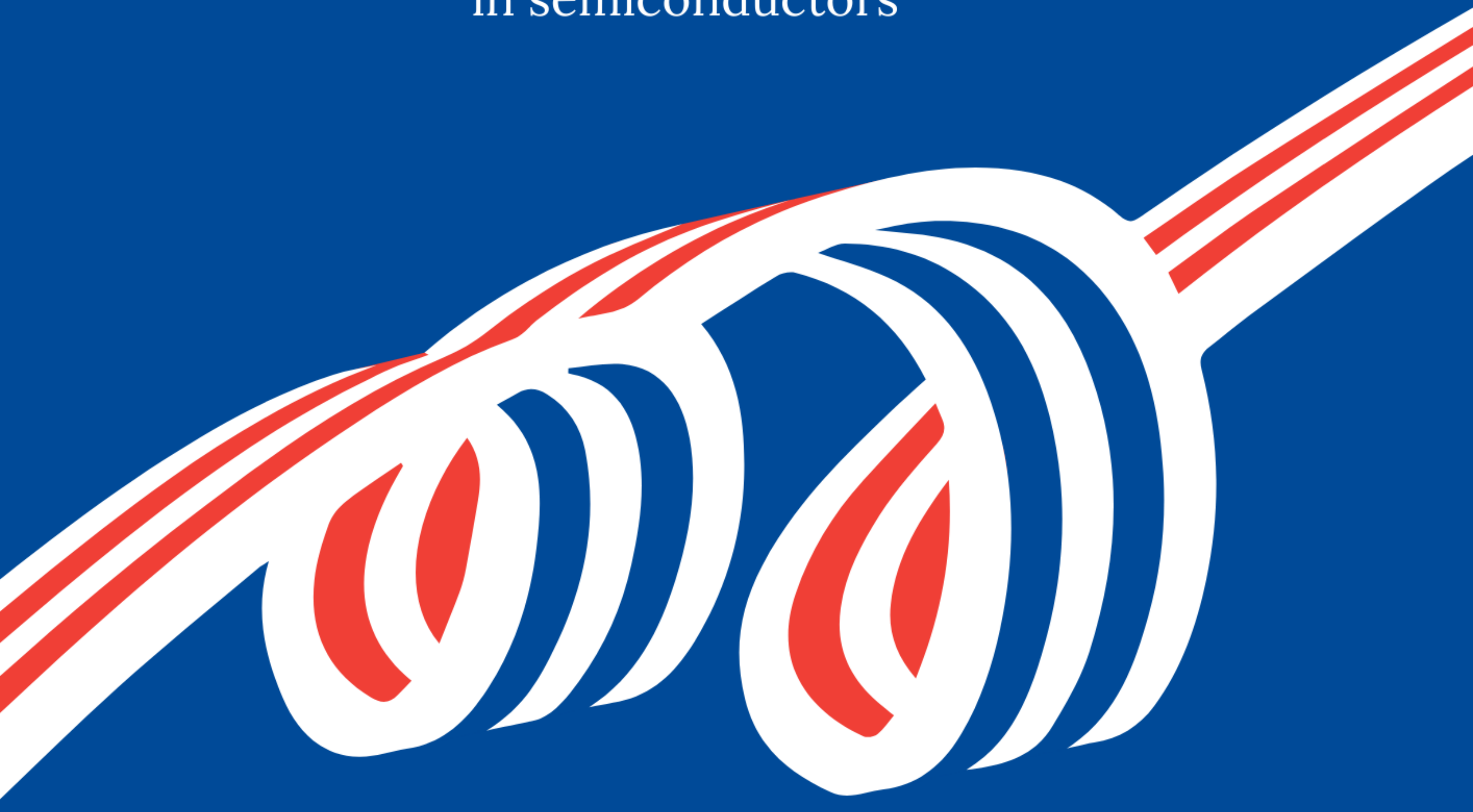
AUGUST 2021 MASTER THESIS

A framework for Artificial Intelligence Organizational Readiness

An exploratory study of influencing factors in semiconductors



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MSc Management of Technology

"Pain + Reflection = Progress"

-Ray Dalio, Principles

A framework for Artificial Intelligence Organizational Readiness

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Executive summary

The applications of artificial intelligence (AI) are significant on a social and economic scale, and they can offer businesses great value and opportunities. However, due to AI's varied application areas, its inherent complexity, and the new organizational requirements that result from AI adoption, companies encounter pitfalls when deploying the technology. Potential implementation scenarios are not always clear. Understanding the AI readiness on an organizational level which indicates “the extent to which an organization has the ability to reap the benefits of AI” can improve the chances of effective AI deployment. This is critical for realizing AI's business value.

As of now, there is not much research on organization's readiness for AI. Moreover, the current frameworks do not incorporate context-specific considerations for organizational readiness. This research aims to investigate the organizational readiness of AI with empirical evidence in the semiconductor industry. It is a critical step in avoiding costly failures considering the capital-intensive characteristic of the semiconductor industry.

This study proposes an AI organizational readiness framework and conceptualizes 20 empirical readiness factors in six dimensions. To achieve this, a literature study has been conducted at first to review the existing AI organizational readiness framework. Then 8 external expert interviews are conducted to give a more holistic view of AI use cases across the semiconductor value chain as identify the opportunity is the first step to establish AI readiness. Three challenges of AI deployment are summarized and the potential AI organizational readiness factors found in the industry expert interviews are listed to guide the case study interviews. The case study is carried out in ASML, one of the leading producers of chip-making equipment in the world.

AI use cases across the semiconductor value have been investigated to provide more background knowledge. This study finds that AI can be applied to automate the chip design and verification process to improve design efficiency and accelerate the production ramp-up. In the manufacturing process, predictive maintenance, pattern modeling, defect inspection, virtual metrology, and statistical process control are some typical AI use cases to optimize the process and improve the yield. Moreover, there is a trend of design collaboration among EDA companies, equipment vendors, and foundries to make manufacturing-ready designs and shorten the build-and-test cycles. In addition, unit traceability throughout the chip life cycle that is driven by the auto chip can help connect the data currently siloed at the individual manufacturing steps

and troubleshoot the problem. AI will also enhance other business functions, for example, capacity planning, demand forecasting.

In the end, a final organizational readiness framework with 20 readiness factors in 6 categories is developed based on qualitative data analysis from 14 case study interviews. In the **strategic alignment** dimension, there are 1) needs and added-value assessment, 2) bottom-up proposal/innovation lab, 3) top management support, 4) business model innovation. In **resource** dimension, 5) talent, 6) financial budget, 7) IT infrastructure, 8) competence center are identified. In the **process** dimension, there are four readiness factors: 9) multidisciplinary team/collaboration, 10) agile way of working, 11) employee training, 12) business process standardization. Regarding **data** dimension, 14) data availability, 14) data governance, 15) data platform are included. In the **AI model** cluster, three factors are identified, 16) explainable AI with domain experts, 17) context-aware modeling, 18) model operation. In the **external business environment**, there are 19) peers, competitors, and software vendors and 20) customer demand. Furthermore, 20 propositions on AI readiness in semiconductor organizations are given indicating their positive or negative influence on AI organizational readiness.

This study aims to bridge the gap between academia and practice as most attention to artificial intelligence was paid to modeling steps in academia. Research on applying AI models to real-life problems and realizing business value has received insufficient attention. This study also contributes to the emerging literature on AI readiness on an organizational level with the developed multi-dimension AI organizational readiness framework. It identifies AI-specific readiness factors under the dimensions of "Data" and "AI model" while others are general factors. Moreover, among 20 readiness factors, 10 readiness factors are newly identified such as the agile way of working, competence center, context-aware modeling. Besides, this study provides a holistic view of AI use cases in semiconductor companies and gives an outlook on the opportunities and challenges associated with AI deployment in this sector. Companies that seek to implement AI can use the readiness factors derived from this study as a tool for assessment. This research can also help decision-makers, managers, and project teams to develop and deploy AI faster and more effectively.

Keywords: Artificial intelligence, organizational readiness, semiconductor manufacturing

Contents

Abbreviations

AI	Artificial Intelligence
APC	Advanced Process Control
ASML	Advanced Semiconductors Materials Lithography
CPU	Central Processing Unit
D&E	Design & Engineering
DSS	Decision Support System
DUV	Deep Ultraviolet
EDA	Electronic Design Automation
EUV	Extreme Ultraviolet
Fab	Fabrication plant
GCP	Google Computing Platform
GPU	Graphics Processing Unit
IC	Integrated Circuit
IDM	Integrated Device Manufacturer
IoT	Internet of Things
IP	Intellectual Property
IT	Information Technology
ML	Machine Learning
MoT	Management of Technology
OPC	Optical Proximity Correction
OSAT	Outsourced Semiconductor Assembly and Test
PdM	Predictive Maintenance
PLM	Product Lifecycle Management
SAFe	Scaled Agile Framework
SPC	Statistical Process Control
STS	Socio-Technical System
SVM	Support Vector Machines
TSMC	Taiwan Semiconductor Manufacturing Company
TRL	Technology Readiness Levels

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1 Introduction

1.1 Background

Artificial Intelligence (AI) is a technological advancement with profound effects on economic, social, and political spheres. AI allows computer systems to learn from their experiences, adapt to new inputs, and automate tasks usually done by humans such as analyzing visual information and making decisions. AI will transform many aspects of human life, just like the steam engine or electricity technology did in the past. (Quan & Sanderson, 2018). AI is considered a key driver of the fourth industrial revolution, which is characterized by the advancement in technology that harnesses the power of digital, physical, and biological systems. Organizations will benefit from AI-powered transformation. AI could increase profitability by an average of 38 percent across 16 industries across 12 economies by 2035, resulting in an economic boost of $14 trillion. (Purdy,2017)

A lot of academic attention has been given to artificial intelligence's modeling steps, with numerous proposals for model architectures. But the application of AI models to real-life problems and generating business value is much more than that. (Jin et al., 2019) There is also evidence to suggest that AI research may not have enough impact on the real world (Boutaba et al., 2018). The growing body of academic research in technology-oriented artificial intelligence must be supplemented by a better understanding of the strategic implications and business value realization of artificial intelligence.

From a socio-technical transitions perspective, companies will encounter challenges when implementing AI within their businesses. The Socio-technical system (STS) approach views the interconnected contribution of technology and people, which is an effective way to manage risk and uncertainty in a company (Walker et al., 2008). Social subsystems include organizational structures, which consist of hierarchical structures, knowledge, skills, values, and needs. The interaction between people and technology can result in challenging situations as the STS is an open system and sensitive to outside influences due to its complex environment of operations. (Oosthuizen & Pretorius, 2016) STS stacks are made up of different layers such as “organizational layer (strategy and management of the company), social layer (broad culture, regulatory environment, end-users, and customers), business process layer (business activity-supported process), equipment layers (hardware), operating system layer (integrated system of hardware and software), data management and communications layer (effective use and management of information), application layer (user interface)". [1]

Technical and non-technical problems could all arise as a result of AI deployment. The role of people and organizations in interaction with technology is gaining increased importance. The technical system and the social system should work in harmony to deliver successful products and services (Bednar & Welch, 2020). What's more, the type of selected technology, development, implementation, and usage of the technology is influenced by existing work systems, organizational needs, and existing technical capabilities in the journey of the company's transformation (Tafvizi Zavareh et al., 2018).

Due to the complexity of AI's technical characteristics, the broad spectrum of AI applications, and the interaction of humans and technology, potential implementation scenarios are not always clear. Additionally to developments in AI techniques, the revival of this field is driven by many other factors such as data, which is a critical part. AI projects also require an organizational consideration for success. AI needs to be effectively implemented and integrated in terms of the cost and time to market. Companies should make an adequate amount of preparation before deciding on the intended use of AI and be proactive in dealing with AI's problems to effectively deploy AI. (Baier et al., 2019) Thus an organization must assess whether it has the capability and prerequisites in place to support effective AI initiatives.

It has been shown that organizations are more likely to succeed in implementing innovation when their readiness for change is high (Weiner, 2019). Organizational readiness is generally characterized by several features such as overall motivational readiness (e.g., desire for change), institutional resources (e.g., infrastructure), people attributes (e.g., adaptability), and organizational climate (e.g., clear goal). (Weiner et al., 2008). The goals of readiness models include capturing the starting point and allowing for the initialization of the development process. Readiness models must take into account context and be customized to the relevant environment, i.e. a particular technology (Molla & Licker, 2005). Therefore a dedicated investigation of AI readiness factors is required.

[1] https://www.lucidchart.com/blog/sociotechnical-systems

Organizational readiness for AI can significantly improve the chances of deploying AI effectively and prove crucial for reaping AI's business benefits (Jöhnk et al., 2019). In order to successfully deploy AI, the organization needs to foster AI readiness from the ground up.

In this study, AI organizational readiness is defined as "the extent to which an organization has the ability to reap the benefits of AI".

1.2 Problem definition

The attainment of AI's value promise is contingent on a set of organizational conditions and factors that have received insufficient attention in academic research. As of now, there is not much research on organization's readiness for AI. Only a few studies have looked at the organizational dimensions of AI deployment, such as how the technology is integrated into organizational processes (Ransbotham et al.,2017). Existing studies on the phenomenon, using the TOE framework (technological, organizational, and environmental), shed light on the influencing factors of AI readiness (Alsheibani et al. 2018; Pumplun et al. 2019). Jöhnk et al. (2021) conceptualize AI readiness with 18 factors and categorize them into five aspects.

However, the current research does not consider the context of different industries. The readiness factors may vary across industries. It is necessary to differentiate readiness factors for AI adoption based on the organizational context and goals for more effective AI deployment. Pumplun et al. (2019) suggest additional research such as focusing on or comparing specific industries (e.g., healthcare, banking, and finance) and associated requirements, or in-depth examination of specific departments and use cases (e.g., HR, Service) should be done. Jöhnk et al. (2021) also suggest that it is crucial to consider organizational readiness in light of the context. Up to date, there are a few articles regarding AI readiness in healthcare organizations (Alami et al., 2020). But the study of AI readiness at the organization level in terms of the semiconductor industry has remained underrepresented in the existing literature.

Therefore, an empirical investigation is necessary for the semiconductor industry of the organizational readiness of AI. This is a critical step in ensuring its successful integration considering the capital-intensive characteristic of the semiconductor industry. AI readiness research in this sector can help with avoiding wasteful investments and costly failures.

2 Literature review

An overview of relevant topics is provided in this chapter from a theoretical perspective.

In section 2.1.1, technology adoption and organizational readiness theories are first discussed which provide the necessary theoretical foundation for “AI organizational readiness”. Then existing AI organizational readiness frameworks are discussed in section 2.1.2 and typical readiness factors are extracted from existing frameworks in 2.1.3.

In section 2.2.1, the opportunity of AI in semiconductors is explained in which the characteristics of the semiconductor industry are taken into account. In section 2.2.2, the evolution of process analytics is reviewed and the trend of advanced analytics with AI is introduced. In section 2.2.3, AI use cases in semiconductors are discussed as AI as a tool should be linked with the clear business case.

2.1 AI organizational readiness

2.1.1 Technology adoption and organizational readiness

Adoption of innovation has been studied at either an individual level or at a firm level (Oliveira & Martins, 2011)(Aboelmaged, 2014). Innovation adoption theories: Diffusion of Innovation (DOI) theory, Technology Acceptance Model (TAM), Theory of Reasoned Action (TRA), and the Theory of Planned Behavior (TPB) have been widely used in IT innovation adoption studies. Among these theories, a study suggests that DOI was used more extensively in studies that performed organizational analysis, whereas TAM, TRA, and TPB were used primarily for individual-level analysis. Moreover, the TOE framework has been comprehensively approved for organizational-level studies of IT innovation adoption. (Hameed et al., 2012) Three stages are involved in innovation adoption: initiation, adoption decision, and implementation (Rogers, 2010). For organizational level analysis, Tornatzky & Fleischer (1990) proposed a framework for technological innovation decisions that considered technological, organizational, and environmental factors. This model is known as the 'TOE framework,' and it has become a useful approach for investigating factors influencing IT adoption in organizations. Hameed et al. (2012) proposed a conceptual model for the IT innovation adoption process in an organization by integrating innovation adoption theories with the popular frameworks.

In consonance with technology adoption antecedents, research from various disciplines discusses the concept of organizational readiness for change which is a precursor to the successful implementation of complex changes (Weiner 2009). Several IT readiness models have been proposed and applied to improve competitiveness and maintain resources efficiently (Alshawi,2007). As depicted in Figure 1, the current literature also discusses digital readiness with respect to the adoption of digital technologies. It is essential that the different factors involved in building digital readiness are developed over time, not just a one-time move. (Lokuge et al., 2018).

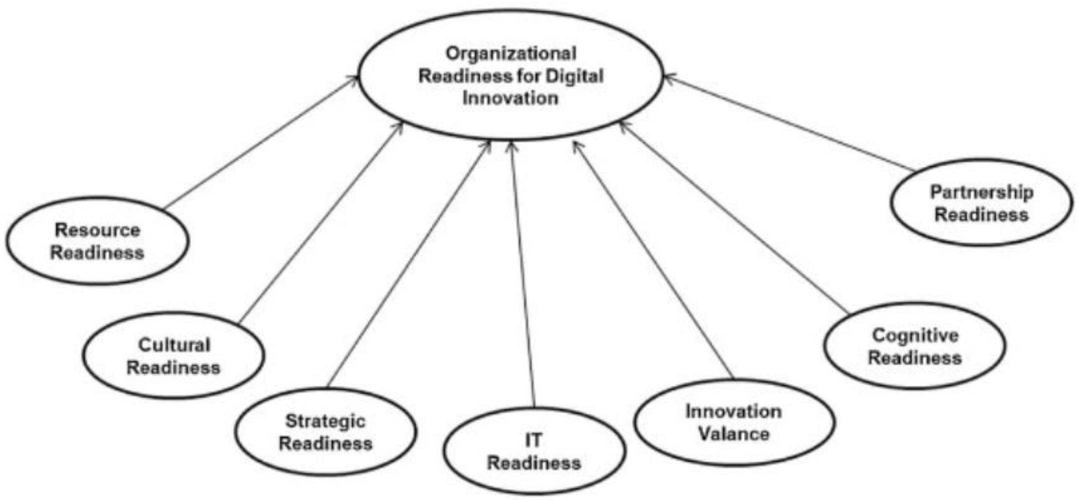

Figure 1 Organizational readiness for digital innovation (Lokuge et al., 2018)

This study focuses on AI organizational readiness, aiming to conceptualize AI readiness and critical readiness factors. Understanding AI readiness can enhance prescriptive knowledge that enables action-oriented indications to build AI readiness. AI readiness factors developed by this study aim to provide the necessary foundation (that can be operated as readiness assessment) for making informed decisions throughout the AI readiness and adoption process as successful AI adoption requires a comprehensive knowledge of important AI readiness factors.

2.1.2 AI organizational readiness frameworks

There are many different ways organizations can adopt AI, depending on their specific application goals. Organizations need to have a deep understanding of AI and determine the appropriate level of ambition for potential applications due to its widespread potential. Furthermore, Because AI adoption has such a diversity of purposes, organizations must adhere to certain conditions and implement specific management practices for success (Hofmann et al., 2020).

Efforts to foster AI readiness must be coordinated at all levels of an organization to ensure successful AI adoption (Baier et al., 2019). Artificial intelligence requires further discussion in relation to the adoption and readiness of technology in organizations due to its special nature and challenges compared to other technologies. However, there is limited research on AI adoption and AI readiness (Alsheibani et al. 2018; Pumplun et al. 2019; Jöhnk et al.,2021). The detailed information of frameworks can be found in Appendix A.

AI readiness is defined as how prepared an organization is to take steps to implement AI applications (Alsheibani et al., 2018). Before adopting AI, organizations are able to identify potential gaps for successful adoption by conducting AI readiness assessments. An assessment of this type of decision-relevant information can be gained through such assessment to reduce uncertainty about the AI adoption decision. Furthermore, AI readiness assessments help organizations determine the resources, capabilities, and commitments needed to meet their AI goals (Alshawi, 2007).

Alsheibani et al. (2018) explore AI readiness using the TOE framework as seen in Figure 2 (Tornatzky et al. 1990). It presents the research hypotheses from the perspectives of technological readiness (relative advantage and compatibility), organizational readiness (top management support, organization size, and resources), and environmental readiness (competitive pressure and government regulatory issues). Furthermore, they believe that high AI readiness has a positive impact on AI deployment success.

Pumplun et al. (2019) extend the TOE framework with AI-specific factors as seen in Figure 3 (e.g., data) to investigate AI readiness and identify subcategories for existing ones (e.g., GDPR and employees' council as part of government regulations).

Jöhnk et al. (2021) conceptualize AI readiness with 18 factors and categorize them into five aspects as seen in Figure 4. Five clusters are strategic alignment, resources, knowledge, culture, and data. Using AI readiness to integrate AI adoption and concepts of technology adoption, additional evidence for the theory of readiness is provided by this article. According to them, establishing readiness once before technology adoption is not sufficient, since the two concepts are closely interconnected and mutually beneficial. While defining readiness and adoption separately, the concepts of both provide an important frame of reference for evaluating the use of technology in organizations.

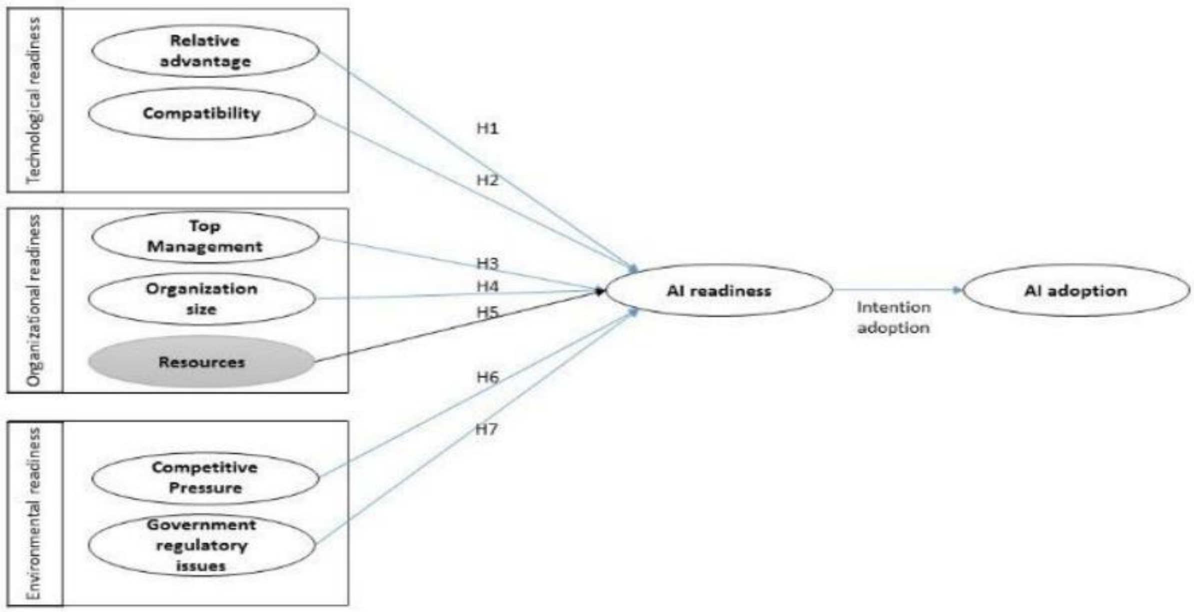

Figure 2 Research framework for AI readiness at firm level adapted from TOE framework (Alsheibani et al. 2018)

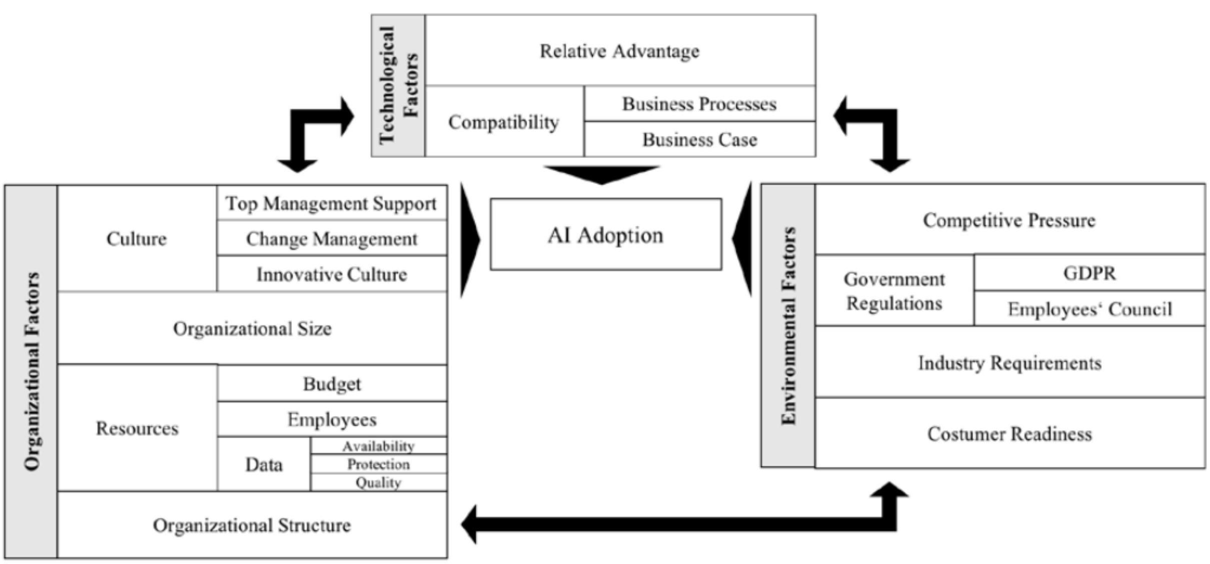

Figure 3 Extended and deepened framework for AI readiness (Pumplun et al. 2019)

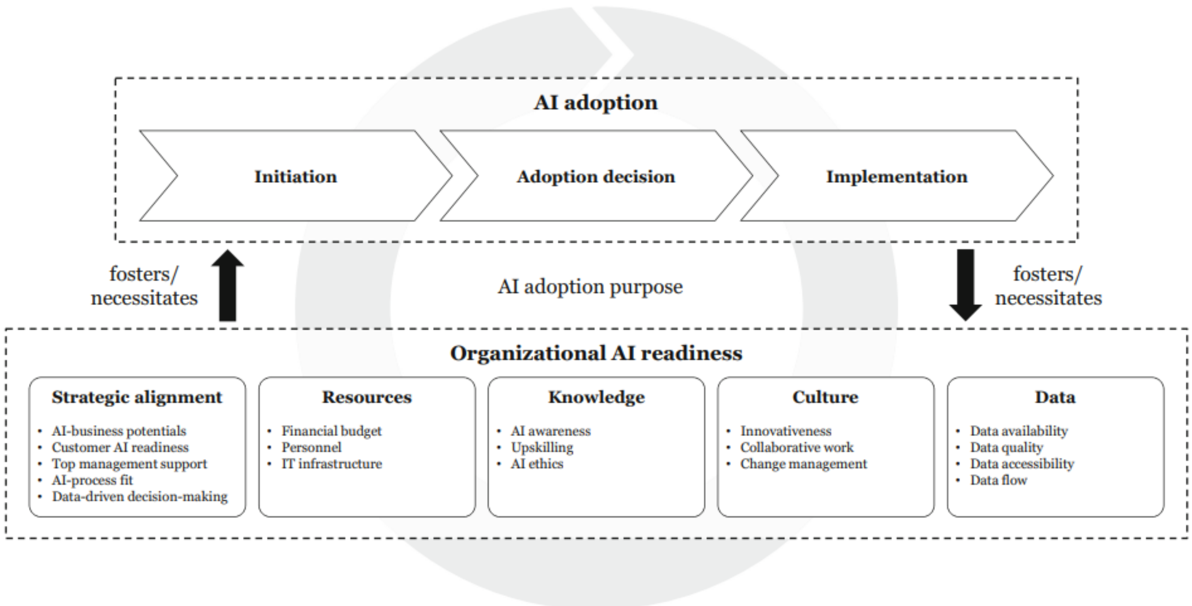

Figure 4 Integrating AI Readiness in the AI deployment Process (Jöhnk et al.,2021)

However, few studies have examined how AI's characteristics apply to context-specific considerations about organizational readiness. A study examines the readiness for artificial intelligence integration in health care delivery and reveals four factors that should be better considered, which are "(1) Needs and added-value assessment; (2) Workplace readiness: stakeholder acceptance and engagement; (3) Technology-organization alignment assessment; and (4) Business plan: financing and investments" (Alami et al., 2020). Developing an organizational readiness for AI in healthcare is critical for ensuring success and preventing unnecessary investments and costly failures. Regarding the context of semiconductor manufacturing, there is no existing literature focusing on organizational AI readiness although there is a wealth of literature on the technical performance of AI applications in the semiconductor manufacturing industry.

To summarize, current research provides useful theoretical groundwork but does not go further into industry-specific organizational AI readiness factors. This research hopes to provide a sound set of organizational AI readiness factors in the semiconductor industry and assess AI readiness using the appropriate indicators.

2.1.3 Typical readiness factors and characteristics

As AI organizational readiness is quite an emerging research field, relevant literature is limited. Existing readiness factors are mainly extracted from three articles (Alsheibani et al., 2018) (Pumplun et al., 2019) (Jöhnk et al., 2021) and one article in AI readiness in healthcare (Alami et al., 2020) is also taken into consideration.

Alsheibani et al. (2018) and Pumplun et al. (2019) both mention “**relative advantage**” that refers to the need of using AI compared to other technologies. They both mention “**compatibility**” which refers to “the fit between the desired application and technology”. Alsheibani et al. (2018) propose “Compatibility between the AI business case and an organization’s existing strategies positively influences AI readiness” and Pumplun et al. (2019) propose “Compatibility between AI technology and business processes as well as the development of a dedicated business case” positively influence AI readiness in companies. Similarly, Jöhnk et al. (2021) propose “**AI-business potentials**” which means the use of AI in an organization should be beneficial and suitable. What’s more, Alami et al. (2020) propose “**needs and added value assessment**” to avoid the negative effects AI may bring to the organization. One thing that shares in common here is that AI should be deployed with a clear **business case (the need to use AI and associated business value)** in mind beforehand.

Alsheibani et al. (2018), Pumplun et al. (2019), and Jöhnk et al. (2021) all mention “**top management support**” as a factor that can positively influence AI readiness as a top leader can coordinate resources to facilitate AI deployment.

Alsheibani et al. (2018) propose “**human, enterprise and technology** resources” are important resources to adopt an innovation. Pumplun et al. (2019) propose three pillars in resources that are **budget, employees, and data**. In the data dimension, **data availability, protection, and quality** are considered. Jöhnk et al. (2021) list three factors in the resources dimension which are **financial budget, personnel, and IT infrastructure,** and put data in a separate dimension that includes **data availability, quality, accessibility, and data flow**.

Alsheibani et al. (2018) propose “**firm size** positively influence AI readiness”. However, Pumplun et al. (2019) find “it is unclear whether larger companies have a better chance of adopting AI” and “**organizational structure**” influences the adoption of AI in companies instead. More specifically, they think a bureaucratically structured organization will hamper AI readiness.

Pumplun et al. (2019) and Jöhnk et al. (2021) both mention the "**business process**" aspect of AI readiness. Pumplun et al. (2019) propose "compatibility between AI technology and business processes (e.g., agile forms of work)" can have a positive effect. Jöhnk et al. (2021) mention "AI-process fit" and propose "AI-based systems are more precise if processes are structured and provide standardized data input".

Pumplun et al. (2019), Alami et al. (2020), and Jöhnk et al. (2021) all mention "**change management**" is important to develop an innovative culture in the organization and let related stakeholders embrace AI. What's more, Alami et al. (2020) think "**appropriate training**" may be involved in building organizational readiness and similarly Jöhnk et al. (2021) mention "**AI awareness**" and "**upskilling**" that aim to provide employees with sufficient AI knowledge and skills.

Regarding environmental readiness, Alsheibani et al. (2018) propose "**competitive pressure**" and "government regulations" are positive factors on AI organizational readiness. Pumplun et al. (2019) find "**government regulations**" as a negative factor as strict laws on data processing and pressure from employee councils can impede the implementation of AI. Moreover, they propose "**Industry-specific properties** (e.g., specific regulations, customer group)" can have either positive or negative influence. Pumplun et al. (2019) and Jöhnk et al. (2021) both find "**customer readiness**" as important but they focus on different aspects. Pumplun et al. (2019) propose "demanding customers will nudge the companies to design individualized, intelligent products" while Jöhnk et al. (2021) propose "organizations need to prepare customers by forming adequate expectations".

Additionally, Jöhnk et al. (2021) propose several new AI organizational readiness factors that are not mentioned in previous readiness literature such as "**AI ethics**" to avoid discriminative results, "**collaborative work**" to combine different skillsets of employees.

Table 1 Typical readiness factor in the existing literature

Readiness factors	**References**
relative advantage	Alsheibani et al. (2018) Pumplun et al. (2019)

compatibility	
competitive pressure	
AI-business potentials	Jöhnk et al. (2021)
AI awareness	
AI ethics	
collaborative work	
data accessibility & data flow	
needs and added value assessment	Alami et al. (2020)
firm size	Alsheibani et al. (2018)
organizational structure	Pumplun et al. (2019)
industry-specific properties	
data protection	
top management support	Alsheibani et al. (2018) Pumplun et al. (2019) Jöhnk et al. (2021)
employees/personnel	Pumplun et al. (2019) Jöhnk et al. (2021)
IT infrastructure	
data availability & quality	
business process/AI-process fit	
customer readiness	
budget	Pumplun et al. (2019) Alami et al. (2020) Jöhnk et al. (2021)
change management	
appropriate training/upskilling	Alami et al. (2020) Jöhnk et al. (2021)

The literature review on typical AI organizational readiness factors has its limitations. Factors are extracted mainly from the three articles mentioned above as existing literature on this topic is scarce. This literature review only considers readiness literature on “AI” and literature related to big data analytics that might have factors in common is not taken into consideration.

2.2 Artificial intelligence in semiconductors

2.2.1 AI opportunity in the semiconductor industry

Microchip manufacturing is one of the most advanced and complex manufacturing processes. In semiconductor manufacturing, semiconductor "wafers" undergo elaborate processing in fabs, where several layers of films are deposited, patterns are applied, and etchings are performed in order to define features in repeated patterns on wafers, called "die". As a result, multiple layers are constructed by revisiting "front-end" processes. The "back-end" processing of an individual die takes place after the front-end processing is complete. This involves assembly, testing, and packaging capabilities. The front-end process requires a cleanroom environment and complex equipment, including oxidation systems, epitaxial reactors, diffusion systems, ion implantation equipment, physical vapor deposition systems, chemical vapor deposition systems, photolithography equipment, and etching equipment. There are usually hundreds of components in each machine, with at least a thousand failure points. Each machine costs more than one million dollars. (May et al.,2006)

With ever-increasing time-to-market expectations under great chip demand and shrinking dimensions due to Moore's law, solving production problems and increasing yield in such a complex production process is getting more difficult. All the steps during the semiconductor manufacturing in fab are monitored thus generating immense amounts of data. As shown in Figure 5, fab-wide data volumes are growing at exponential rates. (Moyne & Iskandar, 2017) With hundreds of thousands of possible production parameters involved, the ever-increasing sophistication of the semiconductor manufacturing process necessitated longer time frames for detecting and localizing equipment faults. (Stanisavljevic & Spitzer, 2016)

Semiconductor companies are facing great challenges to boost performance, cut down on power consumption, and risk increasingly prohibitive design costs at an ever lower node. AI opens up new growth opportunities for semiconductor companies to gain a sustainable competitive advantage. It is now more important than ever for semiconductor companies to consider how to best leverage artificial intelligence and which possibilities make the most sense for their businesses.

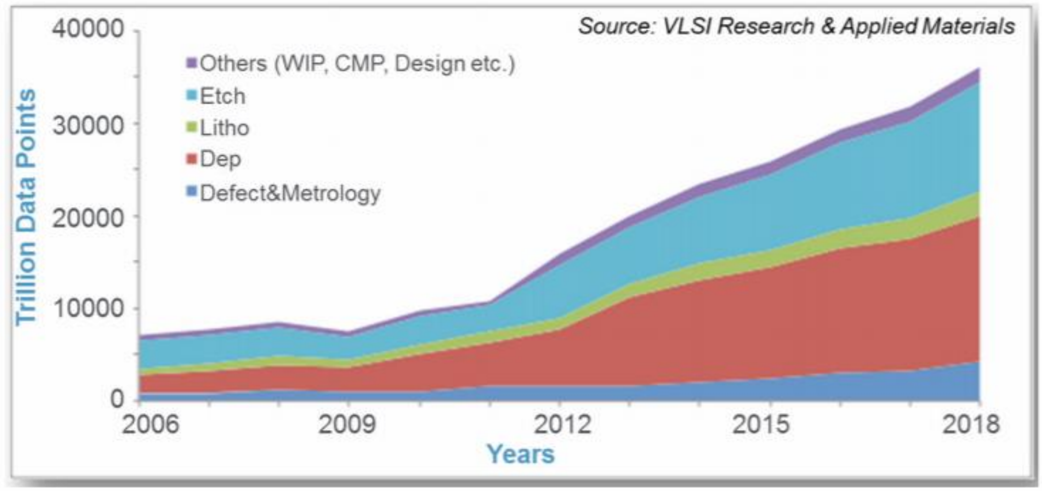

Figure 5 The big data explosion in semiconductor manufacturing (Moyne & Iskandar, 2017)

Unlocking AI's potential can transform what businesses do. According to a technical report, semiconductor industry leaders recognize the significance of artificial intelligence for their industry and are most forthcoming about implementing it as seen in Figure 6, according to the report, 77% of semiconductor executives have adopted or are piloting AI within their companies. In addition, 63% of semiconductor executives expect that AI will be the most impactful on their business over the next three years, compared to 41% of executives from other industries. In addition to distributed ledgers, extended reality, and quantum computing, AI ranked higher for chipmakers in the report than any other disruptive technology. (Daugherty & Carrel-Billiard, 2019)

AI will be a key driver of growth for the semiconductor industry due to high manufacturing costs and the increasing complexity of chip development. Utilizing AI technologies and partnerships can be an effective method for chipmakers to capitalize on this opportunity.

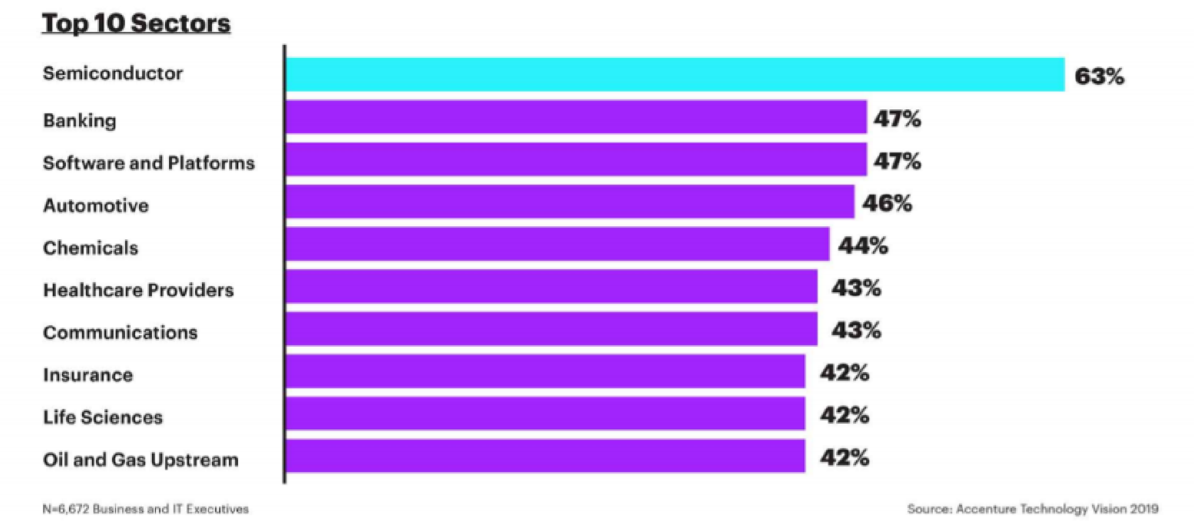

Figure 6 Semiconductor ranks top in ten sectors regarding AI expectation (Daugherty & Carrel-Billiard, 2019)

With machine learning, it is possible to increase semiconductor output yields by up to 30 percent, minimize scrap rates with ML-based root-cause analysis and reduce testing costs with AI optimized fab operations. (Bauer et al., 2017) The ability of AI to carry out preventive maintenance and field force preparation, along with enhancing manufacturing and assembly processes, suggests that it has substantial application opportunities and profitability potential in semiconductors, such as harnessing data to adapt production and supply chain operations can reduce expenditure on utilities and raw materials, reducing overall production costs by 5 to 10 percent in explored use cases (Chui et al., 2018).

2.2.2 The trend of advanced analytics in semiconductor manufacturing

AI refers to the use of technological devices to replicate human cognitive abilities to achieve objectives autonomously while recognizing any constraints that may be experienced (Haenlein & Kaplan, 2019). Machine learning (ML) is the main component of the realization of AI, describing the automatic learning of hidden attributes or underlying rules of data. Its output is used as the basis for independent suggestions, decision-making, and feedback mechanisms which is a way to establish AI. AI and ML are often used interchangeably-especially in a business environment as most AI systems today are based on ML. (Bauer et al., 2017)

In semiconductor fabrication plants (fabs), complex processes, sophisticated equipment, and time limits are employed to meet high productivity fluctuation demands with capital-intensive and automated manufacturing processes. The manufacturing of semiconductors produces tons of data, making it suitable for analytics of big data, and at the same time, annual semiconductor production is rising rapidly. With conventional analytical tools, the big data generating from those thousands of devices at the quantities can simply not be analyzed quickly enough. Semiconductor facilities generally operate at near capacity, so yield optimization is critical for semiconductor manufacturers and they need to use advanced analytics to gain insights on pursuing a high level of quality and reliability to keep the yield at high levels thus remaining profitable in a very competitive global environment. (Wong, 2015)

Advanced Process Control (APC) emerged as a tool in the 1990s and quickly evolved into a requirement in the early 2000s. The evolution of process control can be seen in Figure 7. Three challenges existed in the industry: Equipment and process complexity, Process dynamics, Data quality. Process analytics is therefore a critical component of the majority of fab analytical solutions. (Moyne & Iskandar, 2017)

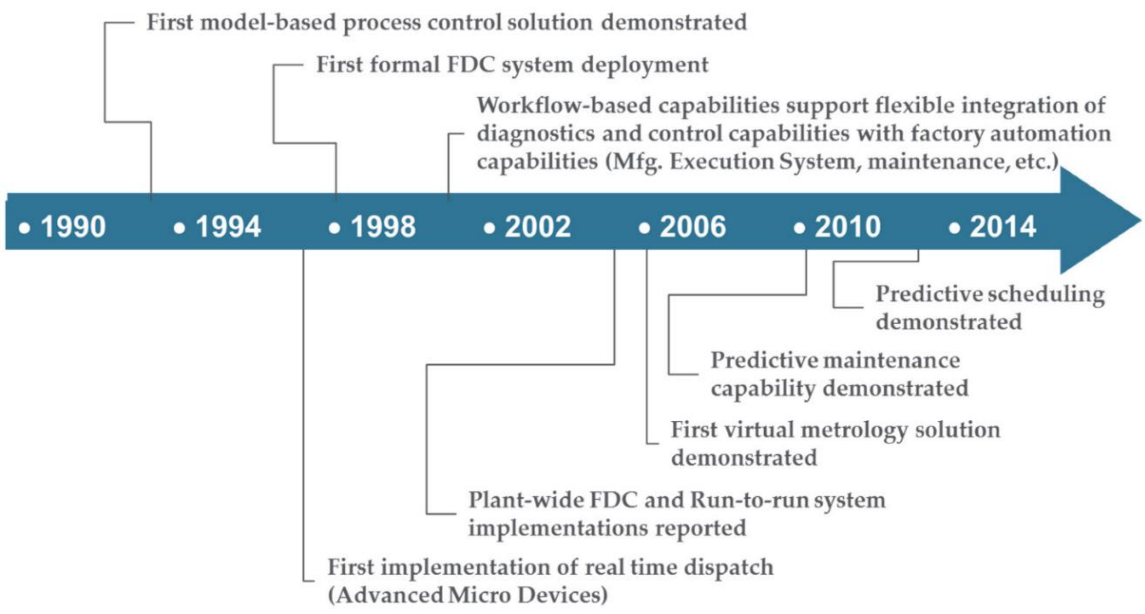

Figure 7 History of process analytics in semiconductor manufacturing (Moyne & Iskandar, 2017)

Now a new approach of the control system which incorporates Advanced Analytics and Artificial Intelligence is emerging and is promising to exceed the performance of the Advanced Process Control approach at a fraction of its cost and complexity. It has several profound consequences. (Somers, 2018) Firstly, AI-based control works incredibly effectively. Usually, expensive APC systems deliver improved results in the range of two to three percent. The efficiency of current APC systems can be improved by an extra one or two percent by AI systems and have enhanced non-APC operated systems by over 30 percent. Secondly, with experiences that may not be well-understood, AI can be extended to dynamic systems. AI applications in real-world systems have recognized problems and opportunities for enhancement that have puzzled even seasoned control technicians. Moreover, it is much easier and more efficient to introduce Artificial intelligence than previous advanced control solutions. It opens up the opportunity for organizations with smaller plants or less traditional processes to use it, especially as the latest generations of development are sufficiently user-friendly to be put directly in the process engineer's hands. Analytical solutions for semiconductor manufacturing require both equipment and process expertise.

Artificial intelligence can be a very useful tool and has a great economic impact on semiconductor manufacturing optimization. A lot of papers on this topic are published in recent years. (Gardner and Bieker, 2000) (Schirru, Pampuri, and De Nicolao, 2010) (C.-H. Lee et al., 2015) The application of AI/ML has significantly shortened the time required to build a system based on expert knowledge and shortened the time required to detect faults, thereby giving engineers more time to optimize the problems in the process (Stanisavljevic and Spitzer, 2016).

2.2.3 AI use cases in semiconductor manufacturing

It is difficult to extract the full benefits of data using traditional approaches. As a result, even the most sophisticated processes do not fully exploit manufacturing data. Today, machine learning techniques are recognized as powerful tools for continuous quality improvement in a large, complex manufacturing process like semiconductor manufacturing. (Shin & Park, 2010)

Predictive maintenance (PdM)

Predictive maintenance reduces the likelihood and cost of equipment failures. In a fab, wafer manufacturing will come to a standstill if just one piece of semiconductor production equipment goes down and is out of operation for hours. Such disruptions are costly as seen in Figure 8, particularly if the factory is running to meet demand on a 24-hour cycle. Keeping the equipment running is critical in semiconductors.

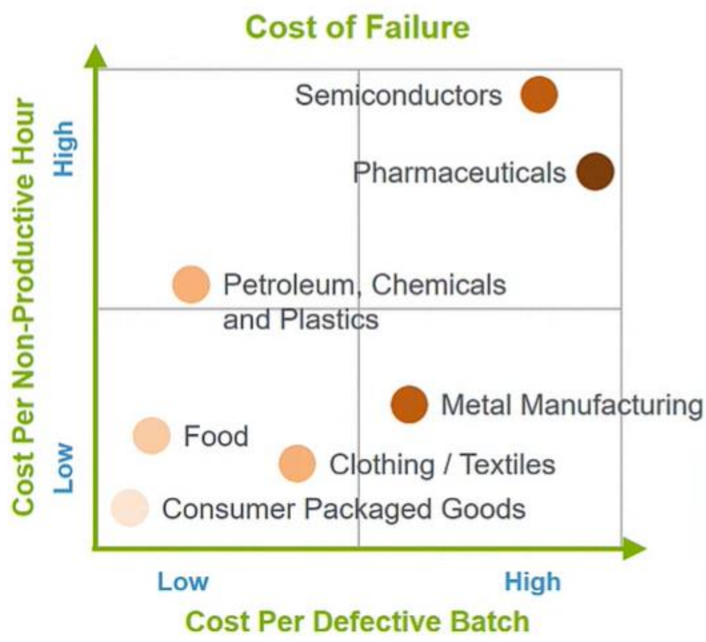

Figure 8 High capital costs of facilities in semiconductors (Applied Materials, 2019)

Predictive maintenance is proving its effectiveness in increasing the rate of return on investment, especially in the prevention of catastrophic events in production that may undermine accounting quarterly performance. (Dorsch, 2018) A major improvement can be anticipated due to improved prediction of failure by contrasting an AI-based approach to conventional condition monitoring or more classical maintenance strategies such as a usage-based exchange. Accessibility can often increase by more than 20% depending on the starting point and the degree of redundancy. The cost of inspection can be decreased by up to 25% and an overall reduction of up to 10% of the annual cost of maintenance is possible. (Bauer et al., 2017)

Statistical process control (SPC)

Yield is a statistical expression of a semiconductor process's quality. It is calculated as the number of functional dies or chips on a wafer, as well as the portion of dies on producing wafers that are not dismissed during the manufacturing process (Gruber, 1994). The majority of the studies deal with the difficulties of recognizing defective patterns to boost up yield (Gallo et al., 2020).

Misaligned image processing can lead to thousands of auxiliary operations and damaged wafers during the photolithography process, wafer scrutiny, and inspection. (Han et al., 2020).

Ineffective image analysis systems cost semiconductor companies revenue growth and noticeably increase their overall expenses (Hsu et al., 2020). To avoid such issues, artificial intelligence techniques can provide reliable, accurate, and rapid wafer and chip pattern locations for wafer inspection, probing, assembly, cutting, and testing equipment. These techniques enable manufacturers to precisely and precisely ensure the quality of wafers and chips, guaranteeing consistent equipment performance along the semiconductor manufacturing process.

The basic statistical techniques for quality control are used in SPC in semiconductors. A control chart maintains the quality and reliability of a manufacturing cycle by using control limits and charts at each node of the semiconductor manufacturing process. This allows engineers to distinguish between normal (systematic) variations and special variations. The most significant advantage of employing SPC in semiconductor manufacturing is the ability to detect systematic and special issues before mass-producing a large number of potentially defective devices.

Virtual metrology

Virtual metrology enables the assessment of performance characteristics powered by data. The use of virtual metrology enables "virtual" control of a single wafer, while it is desirable to avoid routine, expensive, and time-consuming physical measurements.

For example, machine learning techniques can be applied to improve overlay metrology in semiconductor manufacturing. With alignment metrology data, it comes up with a predicted estimate of overlay metrology for each wafer to help reach overlay performance goals. For microchip manufacturing up to and below the 5nm node, such enhancement in overlay performance is essential. (H.-G. Lee et al., 2015)

Using machine learning and tool data, virtual metrology can be used to achieve precise semiconductor photolithography process control. (Tsuda, 2014).

Decision support system

A decision support system (DSS) is a system designed to assist in the resolution of unstructured and semi-structured managerial problems at all stages of the decision process. In the semiconductor industry, decision support systems (DSS) are used to aid decision-making in activities such as material selection, fault detection, and classification. It dates back to 1990s

(Narayanan et al., 1992). Most of the contributions in this field address yield management and fault detection issues (Lin et al., 2004)(Sassenberg et al., 2008)(Weiss et al., 2010).

Researchers use machine learning techniques to discover patterns and hidden relationships to improve semiconductor decision-making. The purpose of controlling the parameters and determining quality is ordinarily made possible by establishing rules for decision-making (Casali & Ernst, 2011). Semiconductor manufacturers are now introducing deep learning techniques on images to enhance the identification process of defects that are challenging for humans to discern. Image data is the most complex type of data that can be trained and also used effectively in AI and, thus, can be used in different areas of production. (Ivworks, 2020)

Capacity planning

Capacity planning is the calculation of a number of tools needed to manufacture forecasted product demands which are challenging in the semiconductor industry due to sensitivity to product mix and uncertainty in future demand (Hood et al., 2003).

Conventional methods of production scheduling frequently necessitate complex calculations and often do not allow for a quick response to changes or short-term adjustments that may occur. Considering the size of a semiconductor manufacturing plant, sensors within manufacturing equipment can produce huge amounts of data. The data could then be used for not only machine control but also for production analysis such as scheduling and capacity planning. Two proposed multi-objective optimization models were proposed (Zhou et al.,2006) to simultaneously determine both planning-level decisions (i.e., capacity allocation and customer service level decisions) as well as operational level decisions (i.e., production, inventory, and shipment decisions).

Demand forecasting

The key step to set production planning is to forecast the demand with more accuracy. As capacity expansion and transformation have long lead times, semiconductor manufacturers must use analytic tools to support manufacturing strategic decisions such as new fab construction, technology migration, capacity expansion, tool procurement, and outsourcing (Chen & Chien, 2018).

Forecasting highly unpredictable demand signals is a key component of effective inventory management in semiconductor supply chains. Support vector machines (SVM) techniques have been used (Chittari et al., 2006). For the proposed demand forecasting procedure to support production planning decision-making, statistical pattern recognition and nonparametric density estimation have been used (Li et al., 2012).

The potential for improvement is still great overall. Semiconductor companies might, for example, provide industrial units with real-time analytics from the Internet of Things (IoT) devices so they could interpret data and send insights to applications that can provide real-time alerts and insights. (Misrudin & Foong, 2019)

3 Research question and method

3.1 Research objective

The objective of this research is to identify AI use cases and explore organizational AI readiness factors in the semiconductor industry. It aims to propose a semiconductor-specific AI organizational readiness framework that can help companies in this sector cross the chasm between industrial practice and AI technology, thus enabling semiconductor organizations to move forward in the field of AI.

3.2 Research questions

3.2.1 Main question

For achieving the mentioned objectives, the main research question of this research is:

What factors influence the organizational readiness for the deployment of Artificial Intelligence in semiconductor companies?

3.2.2 Sub questions

1. What are existing research frameworks on AI organizational readiness?

The answer to this question serves as the starting point on organizational AI readiness research in semiconductor manufacturing by review the existing theoretical framework. The answer to this question is in section 2.1.2.

2. What are the influencing factors of AI readiness on the organizational level in existing literature?

The objective of this question is to find out influencing factors for AI organizational readiness from existing literature. This question is essential to develop the conceptual framework of AI organizational readiness. The answer to this question is in section 2.1.3.

3. What are AI use cases in semiconductor manufacturing to direct the industry-specific organizational readiness research?

This sub-question aims to find out AI use cases in semiconductor manufacturing to show a clear picture of AI applications in the semiconductor industry and indicate overview opportunities. As applications of AI varies across industries, it is essential to know how AI can be used in semiconductors as research on organizational readiness should be embedded with clear purposes. The answer to this question can be found in sections 2.2.3 and section 4.1.2.

4. What are empirical AI organizational readiness factors in a semiconductor equipment company?

With a deeper understanding of the semiconductor industry and AI use cases in this sector, AI organizational readiness framework can be better formulated. This sub-question aims to find out empirical influencing factors of AI organizational readiness in a real-life context by conducting a case study at a semiconductor equipment company. The answer to this question can be found in section 4.2.

3.3 Research relevance

3.3.1 Scientific relevance

This research aims to contribute towards generating theoretical knowledge of AI organizational readiness. First, it aims to find out empirical organizational readiness factors regarding AI deployment and examine those factors in the semiconductor industry. Second, it aims to bring forward the importance of studying organizational readiness to integrate AI into semiconductor manufacturing.

3.3.2 Managerial relevance

In terms of managerial interest, it aims to provide managers with the ability to fully leverage the benefits of AI. This will improve a company's performance, profitability, and competitiveness. AI is also considered not as a single technology, but as an array of various configurations of several different business areas that include multiple key elements that must be made to work together for AI to be successful.

3.4 Research method

A qualitative approach is used in this study. To answer the research questions which were mentioned in section 3.2, several research strategies are required. The first two research questions require a thorough literature review of organizational readiness frameworks and associated readiness factors. The third question requires desk research and expert interviews to identify AI opportunities and find out AI use cases in semiconductors. Then for the fourth question, an in-depth case study will be conducted at a semiconductor equipment company, ASML.

Based on the results of the case study, empirical AI organizational readiness factors can be determined. Thus a conceptual framework for AI organizational readiness can be generated to answer the main research question. Figure 9 shows the process of this research and Figure 10 indicates the conceptual framework of the research.

Deliverables for each sub-question:

Sub1: Theoretical frameworks regarding AI organizational readiness

Sub2: Influencing factors on AI organizational readiness from existing literature

Sub3: AI use cases in semiconductor manufacturing

Sub4: Empirical AI organizational readiness factors in semiconductor equipment company

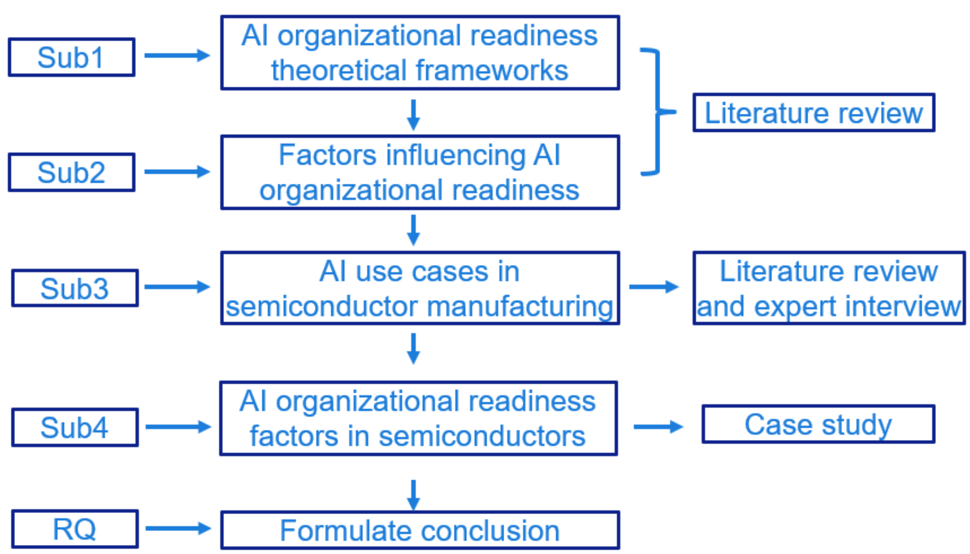

Figure 9 Research process

Figure 10 Conceptual framework

3.5 Data collection and analysis

A literature review is conducted to answer the first two sub-questions regarding AI organizational readiness frameworks and influencing factors. For sub3, desk research is first performed to gain an overview of AI applications in semiconductors, and then 8 experts are interviewed to give deeper insights on AI use cases in semiconductors and what AI opportunities are among semiconductor manufacturing ecosystem players as well as industry insights. Potential readiness factors can be identified through the interviews.

Then a single case study will be done at ASML to find out the empirical AI organizational readiness factors. Researcher Yin (2009) recommends the case study methodology when studying contemporary phenomena within their real-life contexts, especially when the boundaries between phenomenon and context are unclear. This research focuses on artificial intelligence in the semiconductor industry and ASML is one of the leaders among the semiconductor equipment providers. Different AI-related project teams are working on a variety of AI use cases across the whole organization. Therefore, it is considered appropriate to use a single case study strategy that accounts for influencing factors in a business context. To collect data from interviews, the semi-structured interview is used so that a deeper understanding of the situation can be gained. As a result, new dimensions to the research can be added by allowing interviewees to elaborate on their answers. The interviewee's privacy, anonymity, confidentiality, and accessibility will be protected. During the preparation phase, an interview guideline will be created, and an interview instrument pre-test will be performed to ensure that the questions capture the correct information.

The data gathered through interviews are transcribed to analyze the results. Transcribing raises researchers' awareness and increases data transparency. Identities of informants and company names are anonymized to maintain confidentiality.

3.5.1 Industry expert interviews

Experts are selected through AlphaSights which is a third party of knowledge search in order to gain deeper insights on AI use cases in semiconductor manufacturing and how to capture business value on AI for equipment providers. Besides, industry expert interviews aim to find potential relevant readiness factors that could be researched in the case study interviews. 8 experts are from different clusters of the semiconductor value chain with rich industry experience. In the interview, the eight experts refer to their experience in applying AI in semiconductors.

The respondents are chosen based on the selection criteria to ensure reliability. Experts with technology and engineering background must have experience in AI deployment projects. Experts with a business background must have market knowledge of AI. Experts with managerial positions are preferred as they have helicopter views on the company's strategy and project implementation.

Detailed information of experts can be found in Table 2 below. Eight semi-structured interviews are done and expert interview protocol can be seen in Appendix B.

Table 2 Industry expert interview information

ID	Company type	Experience	Interview date and time
E1	IDM	Former Software Engineer, 3+ experience	April 6th, 2021 6:00PM, 48minutes
E2	IDM	Former Head of Global Supply Chain, Assembly Materials Management, 15 years	April 8th, 2021 4:00 PM, 60minutes
E3	Foundries	Former Senior Consultant, 21 years	April 13th, 2021 2:00PM, 60minutes
E4	EDA	Former Vice President R&D, 30+ years	April 14th, 2021 4:00 PM 60minutes
E5	Analytics	Former Sales Executive, 40+ years	April 14th, 2021 5:00PM 50minutes
E6	Equipment	VP Advanced Technology, 20+ years	April 15th, 2021 5:30PM 50minutes
E7	Equipment	Former President, 20+ years	April 28th, 2021 6:00PM 53minutes
E8	Equipment	Former Vice President, 30+ years	May 11th, 2021 6:00PM 69minutes

3.5.2 Case study interviews

ASML is one of the leading producers of chip-making equipment in the world. By developing lithography machines, metrology systems, and software products, ASML enables its customers to follow Moore's Law, and produce ever smaller, cheaper, more powerful, and more energy-efficient semiconductors. During this single case study, data are collected through 14 semi-structured interviews at different departments with people working on different AI-related projects reflecting different AI use cases such as predictive maintenance, statistical process control, scanner performance detection. In the selection of interviewees, the chosen person needs to fall within the inclusion criteria. Interviewees should be working on projects that apply artificial intelligence or advanced analytics and the role of the interviewees are a data scientist, project manager, product owner, or more senior position that have a helicopter view of the organization and projects. The detailed description of the interviewees can be seen in Table 3 and the case study interview protocol can be found in Appendix C. The interview invitation email can be found in Appendix D and an example of categorization of the transcripts for qualitative data analysis is provided in Appendix E.

Table 3 Case study interview information

ID	Project description	Interviewee description	Professional experience	Fulfills interviewee criteria	Interview date and length of the interview
C1	Cognitive research to excavate tribal knowledge	Project manager	8 years	Yes	May 7th 2021 11:30AM, 44 minutes
C2	Data utilization of Application business line	Data Product Manager	5 years	Yes	May 7th 2021 3:30PM, 34 minutes
C3	Scanner performance detection	Senior Technical Program Manager	10 years	Yes	May 10th 2021 1:30PM, 32 minutes
C4	Predictive maintenance	Senior data scientist	6 years	Yes	May 12th 2021 11AM, 25 minutes
C5	Business Insights and Control in Finance	Finance Specialist	6 years	Yes	May 14th 2021 8:30AM, 28 minutes
C6	DUV Scanner Data Products	Director DUV Scanner product	21 years	Yes	May 14th 2021 9AM, 68 minutes
C7	Scanner performance detection	Data scientist	8 years	Yes	May 18th 2021 10:30AM, 26 minutes
C8	Predictive maintenance	Product Owner	8 years	Yes	May 21st 2021 3:30PM, 27 minutes
C9	Machine Learning Product Engineering at Brion	Project manager	18 years	Yes	May 25th 2021 6:30PM, 24 minutes
C10	YieldStar Algorithms & Physical Modeling	Manager D&E Metrology	20 years	Yes	May 26th 2021 2:00PM, 25 minutes
C11	Knowledge Management in D&E	Senior Manager Digital Innovation & Strategy	26 years	Yes	May 26th 2021 3:00PM, 29 minutes
C12	PLM and digital design platform	IT director Competence Center for PLM	26 years	Yes	May 31st 2021 11:00AM, 28 minutes
C13	Inverse lithography	Researcher and Technical Expert	20 years	Yes	May 31st 2021 1:30PM, 27 minutes
C14	Statistical process control	Senior Program Manager & SPC engineer	18 years & 15 years	Yes	June 2nd 2021 2:00PM, 32 minutes

3.6 Validity & Reliability

According to Yin (2009), case study designs must clarify four crucial conditions to enhance research quality. The construct validity, internal validity, external validity, and reliability are discussed in this section. It is important to note that the three validity types are independent of each other.

The construct validity indicates to what extent the method of measurement measures the construct (Gibbert, Ruigrok & Wicki, 2008). To improve it, the researcher should provide evidence for a clear chain of reasoning from the research questions to the conclusion and include more perspectives on the same topic. There are several different perspectives on the same phenomenon provided by literature reviews, expert interviews, and case study interviews. Throughout this thesis's literature review and analysis section, a clear logical chain is established.

The internal validity indicates whether the causal relationship is robust and unaffected by other factors and is based on logical reasoning (Eisenhardt, 1989). The potential organizational readiness factors developed from expert interview data in combination with the existing literature to ensure the findings are internally coherent and systematically related. This served as the basis for interview questions used in the case study interviews.

The external validity of a study indicates the possibility for generalization. This is improved by conducting interviews in terms of different AI-related projects within the organization. The heterogeneity of a sample can enhance its external validity if the same patterns and logic apply to several examples of the same phenomenon (Gibbert et al., 2008).

Finally, reliability calls for minimizing biases and errors in research, allowing other researchers to replicate the same insight if they followed the identical steps. (Denzin & Lincoln, 1994). First, the methodology provides a clear description of the steps to be followed. A case study interview protocol also limits the researcher's bias (Gilbert et al., 2008). Consistency is created among the various case studies by using the interview guide. As a final step, case reports contain notes and interview transcripts. The results can be made available upon request to facilitate retrieval for future researchers (Yin, 1994).

4 Results and analysis

This chapter presents the research results and elaborates on the findings. The results of industry expert interviews are provided in section 4.1 and the results of case study interviews are provided in section 4.2. Then in section 4.3, the proposed AI organizational readiness framework is discussed.

4.1Industry expert interviews

In sections 4.1.1 and 4.1.2, AI use cases across the semiconductor value chain which provide a more holistic view than use cases described in section 2.2.3 are presented. Challenges in AI deployment in semiconductors are summarized in 4.1.3. Potential readiness factors are identified through expert interviews in 4.1.4. The proposed factors are further explored through 14 case study interviews to develop the final conceptual framework.

4.1.1 Semiconductor value chain

To have a deeper understanding of AI's role in semiconductors, a schematic overview of the semiconductor value chain is depicted in Figure 11 through desk research. The manufacturing process for semiconductors consists of three distinct steps: design, fabrication, and assembly & test (Espadinha-Cruz et al., 2021). Integrated device manufacturers (IDMs), such as Intel, perform all three steps in-house. Companies that only design chips and rely on contract chip makers for fabrication are called fabless. Chip designers (fabless or IDM) rely on the design software (EDA) and intellectual property (IP blocks). Foundries such as TSMC, Global foundries manufacture chips in their fabrication plants (fabs). After that, the chip must be tested, assembled, and packaged in a protective manner which is done either by the foundry itself or by outsourced semiconductor assembly and test (OSAT) companies. Fabs rely on a variety of different semiconductor manufacturing types of equipment which are costly from many different vendors such as AMAT, ASML, KLA, TEL, LAM as those companies specialize in particular steps of the fabrication process. For example, ASML produces photolithography equipment which is necessary to transfer a circuit pattern onto a silicon wafer. EDA vendors help fabs and equipment manufacturers research new process nodes and continuously improve them. Some software companies provide end-to-end data analytics to break down the data silos within supply chains and tackle development and manufacturing challenges faced by the semiconductor industry. (Kleinhans & Baisakova, 2020)

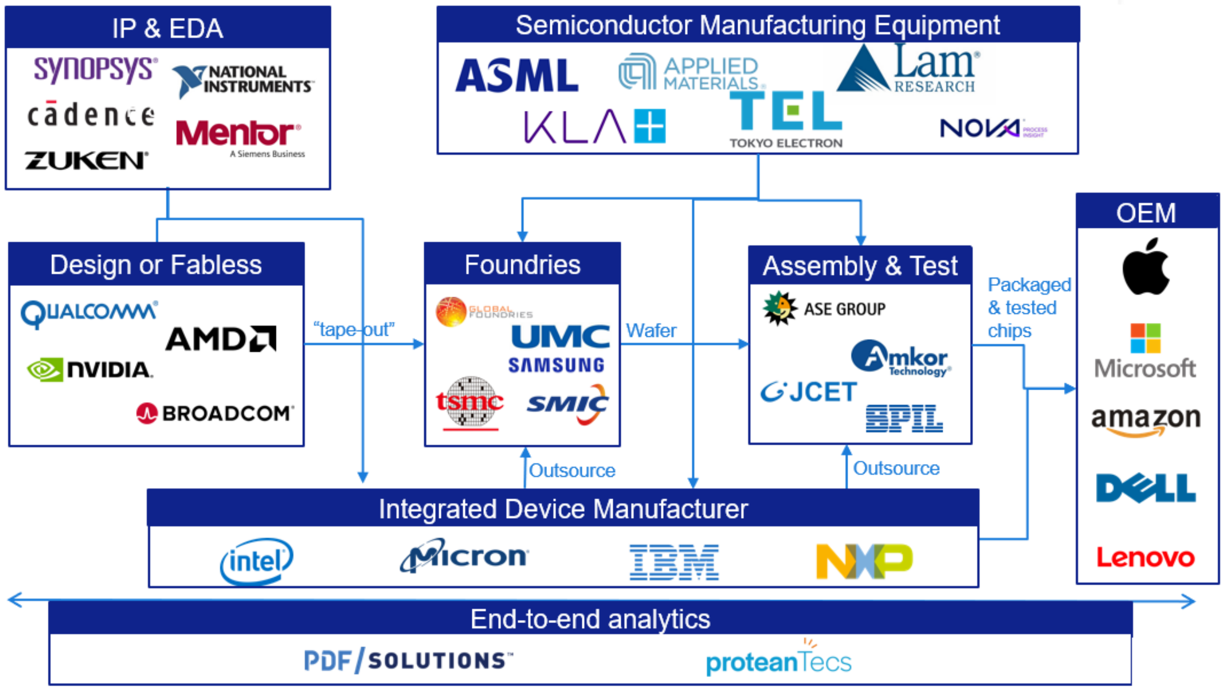

Figure 11 Semiconductor value chain (adapted from Economist, 2018)

AI is a powerful tool to manage process complexity and improve yield rate as semiconductor manufacturing is highly capital intensive and depends on deep process knowledge.

4.1.2 A comprehensive map of AI use cases in semiconductors

Figure 12 is a comprehensive heat map of AI use cases in semiconductor companies from research & design, to semiconductor manufacturing, assembly, and test as well as operations and customer support. More specific use cases mentioned in expert interviews can be found in Table 4 below and associated business value for foundries, equipment vendors, and industry are summarized as well.

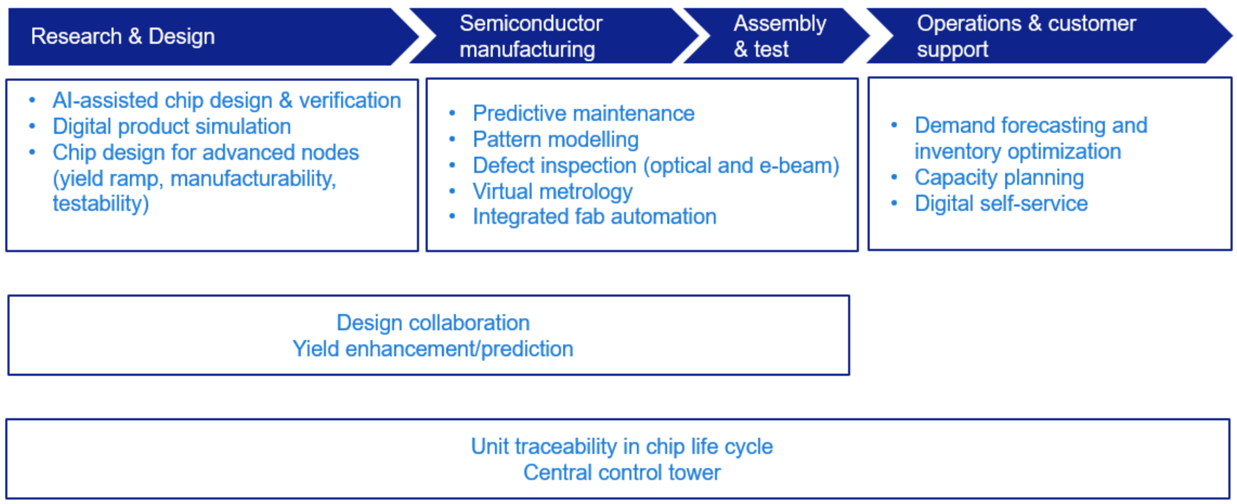

Figure 12 A comprehensive heat map of AI use cases in semiconductor companies

In the research and design phase, It is meaningful to incorporate machine-learning technologies into the IC design process to provide solutions to complex design problems, identify potentially buggy design elements, and facilitate more efficient design flow. In semiconductor manufacturing and testing, predictive maintenance, pattern modeling, defect inspection, virtual metrology can be developed to optimize the manufacturing and testing process. Moreover, there is a trend of a design collaboration between EDA companies, equipment vendors, and foundries to make manufacturing-ready designs and shorten the build-and-test cycles. In addition, unit traceability throughout the chip life cycle can help diagnose where the problem is so that it can be fixed accordingly. AI will enhance other business functions in operations, for example, capacity planning, demand forecasting, and inventory optimization. But they are not specific to the semiconductor industry and are widely used in other industries. Therefore, they can be implemented more quickly.

Table 4 AI use cases mentioned in expert interviews

<table>
<tr><th>Expert</th><th>Mentioned AI use cases</th><th>Business value</th></tr>
<tr><td>E1</td><td>Predictive maintenance; quality control; SPC; demand forecasting; virtual metrology</td><td rowspan="8">• For foundries:
-faster time to market;
-reduced cost of ownership;
-increase manufacturing efficiency
-improve yield rate;

• For equipment vendors:
-shorten the development cycle and ramp fast;
-improve operational efficiency;
-reduce waste
-enhance product performance (availability and utilization)

• For industry and society:
-extend Moore’s law;
-overcome chip shortage;
-reduce energy consumption;
-increase collaboration among ecosystem players</td></tr>
<tr><td>E2</td><td>Foreign material defects detection; Automated packaging to increase efficiency and safety; Drifting detection and prevention; Sorting for fast testing; Defect traceability in the process for testing; Root cause analysis to avoid adding more factories</td></tr>
<tr><td>E3</td><td>Design collaboration; fab automation; Intelligent manufacturing system; Quality defense system to increase yield; Wafer defect inspection; OPC to improve yield; Predictive maintenance to have a higher utilization rate of equipment; Process monitoring in real-time; SPC; digital dashboard; Immediate action to fix those problems; remote control of ultra-clean room by using robotic to prevent contamination and improve safety</td></tr>
<tr><td>E4</td><td>Design synthesis by convert design into a set of gates; place and routing in physical design; help Unsolved problem, 3D packaging; yield prediction and improvement; Defect inspection and process control; optimize process parameters; spectroscopes</td></tr>
<tr><td>E5</td><td>Yield improvement, Real-time analysis at the edge; Predictive maintenance; traceability of chip in the life cycle (Automotive industry trend calls for end to end solution for chip traceability); Design for inspection/self-monitoring chip Less expensive testing</td></tr>
<tr><td>E6</td><td>Defect inspection; process control; virtual metrology; optical critical dimension; guided metrology; guided e-beam inspection</td></tr>
<tr><td>E7</td><td>A real value proposition is integrated factory automation; recipe optimization; Reduce the number of variables; smart factory rapid response platform to replace SPC; predictive maintenance; Reduce defect; AI for marketing</td></tr>
<tr><td>E8</td><td>Process control (Learning-based system when design change); Equipment health monitoring and predictive maintenance; 3D feature measuring with spectral ellipsometer; Guided inspection; predictive design analysis; Ellipsometry measurements to solve 3D issues</td></tr>
</table>

4.1.3 Challenges of AI deployment in semiconductors

From industry expert interviews, three challenges in the deployment of AI-related projects in semiconductors are highlighted. The complete related quotes can be found in Appendix F.

Challenge 1: Conservative attitude towards data sharing

Typically, semiconductor companies are forced to invest significant capital into R&D due to the rapid pace of technological change (Global X ETFs, 2021). Intellectual property is almost the lifeblood of this industry. Thus it is very important to protect their intellectual property. One industry expert mentioned in the interview:

E6: They're very leery to share their knowledge. They all have their automatic process control activities and machine learning and AI groups looking at that stuff. They view that as a competitive advantage.

So semiconductor companies are very concerned about compromising the confidentiality of the information and tend to be quite cautious when it comes to data sharing. Equipment providers can only have limited data access and face data availability challenge as AI development needs a large amount of data. One expert mentioned it is a business limitation nowadays as it is hard to get the players in the semiconductor ecosystem to be comfortable with end-to-end data sharing.

E5: Actually, today, the limitation for really doing that isn't a technology limitation. It's a business limitation. It's getting all that ecosystem to be comfortable and how to share the end-to-end data.

At the same time, there is a slow shift to the adoption of the cloud. Companies are very reluctant to put their designs on the cloud.

E4: Adoption of cloud is another place where, I would say, the semiconductor ecosystem has been much slower to adopt as compared to other industries. There are hardly any tools on the cloud, hardly any EDA tools on the cloud.

Companies prefer to have on-premise servers for data protection and servers should be powerful enough to handle those computing extensive tasks.

Challenge 2: The off-the-shelf solution does not work

Semiconductor manufacturing requires a high level of accuracy and there are hundreds of parameters within each step (Esmaeilian et al., 2016). Also, data are generated explosively at more advanced nodes.

E2: So when we have the 7 nanometers go to 5 nanometers, and in comparison to previous nodes, they are increasing about three times the data size.

According to the experts, the semiconductor industry is a process industry as each step is critical to producing the final product with high quality. In the whole process, collected data can amount to trillions of bytes.

E3: They have a lot of data generated every day, so every day they maybe have generated a trillion of the byte of data will be accumulated. You can understand the semiconductor industry is a process industry, every process is critical and matters.

All these features add operation complexity in terms of AI applications. Commercial off-the-shelf solutions do not work most of the time as it requires deep knowledge of the tools that is hard to gain from third parties. Moreover, the AI solution for one tool might not be applicable for another and you have to develop a context-specific framework for each use case.

E4: all the development is in-house because it does require a fair amount of knowledge about their own tools, which is going to be very difficult to acquire from outside.

Furthermore, another challenge here is to achieve fab-level automation that integrates all kinds of equipment along the manufacturing process. An expert mentioned such a situation:

E7: That's another big challenge in terms of getting that visibility and usability across the fab itself, not just within the tool itself.

A higher level of integrated automation can lead fab to have higher yields, shorter time cycles, and less operating costs. This would be extremely difficult for external companies that provide commercial-off-the-shelf solutions without an in-depth understanding of semiconductor manufacturing and fabs itself also invest a lot to develop automated process control with in-house teams.

Challenge 3: AI intrinsic challenge – probabilistic rather than deterministic

AI and ML techniques mean is the ability to learn from a given set of data and make predictions about future data. According to the fourth interviewee, trustworthy data is essential as the input for the AI model should be of high quality and non-biased otherwise predictions can turn out to be incorrect at first. Secondly, predictions, by definition, are never 100% accurate. Every decision that an AI system makes is a probabilistic decision and there is a level of confidence in the output.

E4: The application to which you apply AI needs to have the tolerance to absorb a probabilistic decision. If your application requires a certain decision or, as it is called in the computer science literature, a deterministic answer, then you will not be able to apply AI to it, because AI techniques of all forms only give you a probabilistic answer.

As a result, the developed AI application or the system must be able to accept a probabilistic answer for that specific use case. What we can do is to fine-tune the AI system and make it better to increase the probability as close to 100% as possible.

These limitations are inherent to AI solutions. There is a certain degree of risk regarding the adoption of AI mentioned by an expert.

E6: I think that people believe that there's value in that and that there's a direction to go. But at the same time, people are kind of conservative that there's a barrier to actually doing that, given the risk of the yield excursion.

So there is difficulty taking the process engineer out of the loop if the system is not fully trusted by humans. Data is analyzed by process engineers using sophisticated software tools and decisions are made on whether and when the process tools need to be adjusted.

4.1.4 Potential AI organizational readiness factors

Interviews with industry experts provide an in-depth understanding of the AI use case and challenges in the deployment. Besides, it also helps with developing AI organizational readiness factors.

Regrading the challenge of data sharing, several existing AI organizational readiness factors resonate with this challenge. AI models require a lot of computing power due to the enormous amount of data they deal with. Thus, **IT infrastructure** can highly influence AI development and at the same time upgrading such hardware is costly. IT infrastructure provider has its advantages in managing IT infrastructure to deliver the value of AI (E1, E2).

Data availability is crucial to develop AI models and is a big challenge currently in semiconductors according to the interviewees (E1, E4, E5, E6, E8)

Most semiconductor companies would like to have an in-house team to build AI capability which requires a significant investment initially. **Support from top management** is needed to kick off a project (E3, E8). From a strategic perspective, support from the executive team is necessary to integrate AI applications into the company's strategic roadmap.

In terms of big companies, they need to spare **budget** (E4, E6, E7) for hiring **talents** (E3, E4, E5, E6, E7) and setting up development environments. It is hard to see the benefits of AI if a company starts with a tight budget and small team. Furthermore, there should be a continued investment in AI for research and development.

In addition, a clear **business case** (E1, E2) should be in mind to guide the whole process and make sure AI application is beneficial for the organization. A **cross-function team** is needed in the development process mentioned by an expert (E2). The **agile way of working** is also beneficial to shorten the time for development (E1).

Moreover, it has been found from the case study that **employee training** (E1, E2, E4) needs to be provided to equip the workforce with essential AI skills to work with intelligent machines.

Regarding the AI model part, **unbiased datasets** (E4) are essential. If data is biased, the prediction or the output of the AI system will be biased and inaccurate. Experts also mentioned the unpredictability of the AI model. There is a need to have an **explainable AI model with a measurement** (E1, E4) matrix to monitor the performance of the model and gradually increase the confidence level or trust.

There is a **Customer demand** (E3, E6) from foundries as they want better tool performance and lower cost of ownership. But the willingness to collaborate with equipment vendors varies among foundries. **Competitive pressure** (E5, E8) exists in the semiconductors in the AI domain. Companies are competing with each other to develop a better AI model and bring it earlier to the market.

It also has been found that equipment vendors attempt to charge extra for the enhanced product with AI capability. Thus, they adjust their **business model** (E6, E8), for example, service contract to ensure the availability of the tool, software licenses for additional software as the complementary for hardware.

The potential readiness factors identified from industry expert interviews (see Table 5 for detailed information) will be further explored through a case study at ASML, a semiconductor equipment company specializing in the development and manufacturing of lithography systems.

Table 5 Potential readiness factors identified from industry expert interviews

Potential readiness factors	Quotes from industry expert interviews
Business case	E1: They require a lot of well-thought POC processes, the **proof-of-concept processes**. If it proves effective, they have grounds to convince the management or convince the other part of the quality engineering team to expand their models. E2: You have to keep showing how **AI is helping** and what it's doing and what the next steps are and what the plans are, and getting feedback, and then **continuing improvement**.
Top management support	E3: So the decision is coming from **top-down**. We have **set up this AI team and are expanding** more and more. E8: So if you're starting something from the in-house, you're going to have to have some **real value participation from the executive team**. And from strategy development, you want to integrate it to whatever the company is providing beyond just that AI software. I think with the semiconductor equipment players, with the semiconductor manufacturing players, this is something that has to **come from the top**.
Talents	E3: It will require **more and more people**, experienced people, and equipment prior and our engineer and our IT people to try to get a lot of tools to helping those kinds of things, controlling and the best practice. This is a very important thing when we are developing those kinds of things, the AI-related program will get much more, much more inside of the semiconductor industry. E4: What you should be able to see from the outside, is the **total investment in terms of people** that they are doing on AI. E5: We want to start **hiring the expertise in the organization** and have them start sorting out and finding these needles in the haystack. E6: But without a doubt, **to the extent that you can hire the talent to do it**. E7: Because if you start so small, I've worked with some players that had five or six people in-house, that were very, very bright, but they could never get the critical mass.

Financial budget	E4: What you should be able to see from the outside, is the **total investment in terms of dollars** that they are doing on AI. E6: There are opportunities to continue to develop upon and improve upon whatever it is that you're doing, but it requires I think **continued investment** and elements of research E7:When you are part of a bigger company, and ultimately you have to hire 20 or 30 folks that are PhD.s in mathematics and advanced software development, etc., you need the **sponsorship**.
Employee training	E1: the company started **offering a lot of internal classes** regarding this data science or AI models as well. All the engineers are required to take these courses and get accredited. E2: I would then **train the individual** to be able to use it effectively and be able to analyze and receive the information to help their job be more effective. E4: I certainly predict, 100%, that the engineers of the future will require **training on using the AI algorithms**. A few people will obviously have to be trained on creating and implementing the algorithm, but not everybody.
IT infrastructure	E1: Because of the sheer size of the data, and also a lot of the dependencies of these models on **huge computing capabilities**, actually **setting up the necessary IT infrastructure is very costly**. Since there's a huge need for this data science attempt in semiconductor manufacturing, they're in a sense **outsourcing it to a lot of IT vendors** as well. E5: IT organizations are starting to realize it's better to let their **infrastructure provider run and manage that and configure that and upgrade** that themselves and to pay for it.
Cross-function team	E2: The way that it works, think of it you have a team lead. You then have people from Manufacturing usually, people from Software Solutions, people from the Automation group, from the Module, meaning Equipment Experts. Then you have Process Experts. This is a process that goes through that equipment. Then you'd have usually Finance, and Supply Chain would be the other.
Agile way of working	E1: It's mostly on **agile-based development**. Basically, a small team where each of the engineers is assigned a different part of the development. There are actually very **quick development processes** to test out and deploy.
Data availability	E1: A lot of the algorithms or data science projects are meaningful only when they have a **full set of data set**, meaning that they have data from certain equipment or data from other equipment. E4: **Data is king**. Whoever has the data has hold of the advantage. It's only now that they start capturing the data. **The more data they have, the better the learning and output will be.**

	E5: Look at the data and then figure out if there's a way that they can do correlations on the data. It **requires really big databases** to go through. E6: The challenge with all of the stuff around yield management and process control is **getting data from the customers.** E8: And AI is intrinsically **dependent on the training dataset**, and the training set is invariably owned by the customer.
Unbiased datasets	E4: The data on which the AI algorithm is trained must not have any bias. It **cannot be biased data**, because that would immediately make the prediction biased as well, and hence the trust would go down.
Explainable AI model	E1: The **unpredictability**, or the fact that you can't really guarantee the performance of the model during the actual manufacturing. E4: There will have to be a **measurement of what the AI algorithm predicts** or things that have already been done. Let's see if the AI algorithm predicts something which matches with the ground truth. That step is extremely important, and that step has to be done on a process node that is already stable and has been around for some time and for which data is available because that is what will **increase the confidence level, the trust level**
Customer demand	E3: So we are **requiring the equipment manufacturer**, for example, AMAT and Lam Research helping us. E6: The degree to which they'll work with the equipment manufacturers is variable and challenging. Fabs ultimately look at **cost of ownership** around any kind of tool purchase.
Competitive pressure	E5: They all have teams of people that want to provide their customer's preventive maintenance algorithm programs. They all want to enhance their business by having more AI types of products, more software types of products. It's **getting the product faster than your competitors** can, which wins you more business. E8: And you're **in a race with your competitors** to see who's going to **converge first and converge on the best model.**
Business model	E6: What everyone really wants to be able to do is actually treat it as an **additional line item, something you could charge** for, advanced algorithm capability. E6: They're getting a **fixed revenue for keeping these tools up**, so if they can lower the cost of doing that, that helps their bottom line. E8: But pure **software licenses** do not make up anything like the bulk of those revenue streams. They are always **sold with a piece for hardware**.

4.2Case study interviews

Through 14 case study interviews, 20 influencing factors in total are identified to form the AI organizational readiness framework. For each case study interview, a transcript is made to do qualitative data analysis to extract readiness factors that are shared in different interviews. The distribution of 20 readiness factors and characteristics of each influencing factor are provided in section 4.2.1. Empirical findings of 20 AI organizational readiness factors are presented from 4.2.2 to 4.2.6. The complete related quotes are listed in Appendix G. The proposed framework is provided in section 4.2.7 where general and AI-specific readiness factors, and the use of the framework are discussed.

4.2.1 Overview of 20 readiness factors in 6 dimensions

The detailed information for each case study interview can be found in Table 6. For each readiness factor, blue blocks mean that a relationship is mentioned in the case, while grey means it is not mentioned. The times of each readiness factor mentioned in case study interviews can be seen as well. The description of AI organizational readiness factors in the final framework can be found in Table 7.

Table 6 Distribution of 20 readiness factors identified from the case study

Blocks in blue are mentioned by interviewees and blocks in grey are not mentioned

Dimension	No.	Readiness factor	Times	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14
Strategic alignment	1	Assessment of needs and added value	14														
	2	Bottom-up proposal/Innovation labs	5														
	3	Top management support	3														
	4	Business model innovation	9														
Resources	5	Talent	3														
	6	Financial budget	6														
	7	IT infrastructure	14														
	8	Competence group	8														
Process	9	Multidisciplinary team/Collaboration	12														
	10	Agile way of working	9														
	11	Employee Training	6														
	12	Business process standardization	5														
Data	13	Data availability	9														
	14	Data governance	10														
	15	Data platform	7														
AI	16	Explainable AI with domain expert	12														
	17	Context-aware AI modeling	6														
	18	Model operation	7														
External environment	19	Peers/competitors/software vendors	6														
	20	Customer demand	7														

Table 7 Summary of 20 AI organizational readiness factors in the case study - inspired by Jöhnk et al. (2021) Table 1

Dimensions	Nr	Readiness factors	Characteristics
Strategic alignment	1	Assessment of AI needs and added value	There is a wide range of applications for AI functions. AI should be considered as a tool with a clear purpose rather than being viewed as an independent entity. To make sure AI will be a good fit for your organization, it is essential to assess its needs and added value.
	2	Bottom-up proposal/ Innovation lab	People with in-field experience are more likely to identify business cases that can be improved with data and AI techniques that have value for the company and customers. Innovation labs can be a way to examine the potential of AI to solve client problems outside of traditional product development. It can boost innovation and tech integration within the company as well.
	3	Top management support	Leadership support makes AI decisions more strategic and facilitates AI initiatives. For AI initiatives to be successful, top management must provide support for the activities needed by mobilizing resources and promoting innovation culture across the organization to make the general atmosphere more positive around AI.
	4	Business model innovation	There is an increasing trend of servitization in semiconductors. Equipment makers can provide AI-enabled service to customers with a new business model to capture more value and gain predictable revenue streams. It can reduce upfront costs for customers in high-capital equipment investment.
Resource	5	Talent	AI deployment requires a broad range of different roles and expertise, including data scientists, machine learning engineers, and domain experts, etc.
	6	Financial budget	AI-based systems require significant investments as assets should be tailored to the particular context and data. By strategically allocating financial budgets for AI adoption, initial obstacles and uncertainties can be overcome.
	7	IT infrastructure	A company's success with AI will be largely determined by its ability to support such robust applications in its IT environment. Data storage requirements and workloads are high when deploying AI. The availability of computational resources, such as CPUs and GPUs and the ability to scale storage as the volume of data grows, are essential for enabling AI-related activities and integrating artificial intelligence.
	8	Competence center	A variety of stakeholders might be involved in AI implementations in organizations and there may also be organizational silos among different AI-related projects that hinder knowledge sharing on AI know-how. The establishment of an AI Competence Center can optimize the development of AI capability and operational efficiency by centralizing AI expertise.

Process	9	Multidisciplinary team/Collaboration	Artificial intelligence development is a multidisciplinary endeavor that integrates data, domain knowledge, and information technology perspectives. Multidisciplinary team or collaboration across different departments enables employees to work together and combine different skills to lead a successful project
	10	Agile way of working	Agile makes sense when it comes to advanced analytics and AI, where iterations are most effective in identifying poorly defined solutions. Using agile approaches for developing AI results in significant advantages for companies, including faster time-to-market, the ability to rethink and fail quickly, and improved collaboration across departments.
	11	Employee Training	The purpose of employee training programs is to equip the workforce with the necessary AI skills to become proficient in the use of intelligent machines. It is only when both the company and employees have an opportunity to meet their common aspirations in the workplace that it becomes feasible to make the transition to an AI-enabled environment.
	12	Business process standardization	To ensure the effective deployment of AI, changes in business processes should be improved towards data-driven and more unified. Task priority should also be predefined to avoid chaos.
Data	13	Data availability	Various types of data and massive amounts of data are used in AI-based systems. Data availability within the organization and data shared by customers fuels AI solutions
	14	Data governance	An overall framework dealing with the management of data and a company's control over the quality of the data with consistency, accuracy, accessibility, completeness, and the risk involved with protecting privacy, security, and compliance can help establish data readiness for AI development.
	15	Data platform	An enterprise data platform enables data to be managed, accessed, and delivered to targeted users to build data applications for strategic business purposes. With a proper data platform, the complexities of developing enterprise AI applications can be reduced and the AI development cycle can be accelerated to achieve fast delivery.
AI	16	Explainable AI with domain expert	In explanation AI, the output of the solution is understandable by humans. It would be extremely difficult to troubleshoot the model if it goes wrong without explainability. Domain experts that have a fundamental understanding of the model is a key differentiator in AI game.
	17	Context-aware AI modeling	Generally, it is more cost-effective to train a general and versatile machine learning model than to train several specialized machine learning models for different operating situations. In contrast, as the volume of training information increases, the likelihood of producing skewed results increases. Therefore, it is important to have models that are context-aware and flexible.

	18	Model operation	Model operation is focused primarily on the life cycle management of a wide range of operationalized AI models. Incorporate AI models into production applications by bringing into account how models behave and change, as well as the processes for building, testing, and evaluating the models.
External business environment	19	Peer companies/competitors/software vendors	External business push accelerates AI development
	20	Customer demand	Demanding customer is an accelerator for the company to build AI solutions.

4.2.2 Strategic alignment

4.2.2.1 Assessment of AI needs and added value

There is a wide range of applications for AI functions so it is important to know what a business case is and why AI is a good fit for the application and the organization (Alami et al., 2020) (Jöhnk et al., 2021). The use case of any product or service should be related to its value. AI should be considered as a tool with a clear purpose rather than being viewed as an independent entity (Pumplun et al., 2019).

All 14 interviewees mentioned needs and added-value assessment as important when making decisions.

C2: So it's the ***use case*** *that has to be connected to the* ***value****.*

Several questions should be considered to do needs and added value assessment according to interviewee C6. For example, what are the problems encountered in semiconductor manufacturing and equipment development? What makes AI a good option to solve the problem and meet the needs in that case? How large is the market for this AI-driven product or service? How much value can be captured with this application?

Customer opportunity should be identified and then it's time to think about how to capitalize on the opportunity with the best solution (C3). AI is one of the elements that can address the issue. The tenth interviewee mentioned:

C10: For us, it's important to develop the best tool. And if AI is helping there, I'm fine using it. If artificial intelligence is too cumbersome and we need to go to physical models

What's more, quantitative value or at least qualitative value assessment of the proposed use case should be thought of carefully before the kick-off (C4, C5). For example, predictive maintenance as one of the AI use cases is useful for many different reasons. It will increase the availability of the machine and reduce the unscheduled downtime for customers. On the ASML side, it is also helpful to optimize the planning and reduce the stock as less maintenance needs to be performed. What's more, labor costs can be saved as less manual effort is needed.

But before industrializing the solution after a few months' trials, you need to reassess the business cases based on some kind of proof in the trial phase. The 12th interviewee mentioned:

*C12: So the result after let's say three months of experimentation is that we can do a really **good business case analysis** and **decide** from that moment on, do we want to proceed with this kind of technology, or do we just stop.*

In this way, the project is more likely to implement the necessary changes to achieve full benefits while avoiding negative consequences.

Proposition 1: Assessment of AI needs and added value positively influences AI organizational readiness.

4.2.2.2 Bottom-up proposals/Innovation lab

A good business case should be identified at first to explore the opportunity of AI (Pumplun et al., 2019). It has been found from the interviews that ASML has established some innovation labs to explore new technologies and related use cases that ASML can benefit from.

People with in-field experience are more likely to identify business cases that can be improved with data and AI techniques that have value for the company and customers (C5). Having innovation labs or topic teams can help the company with rich ideas on AI use cases and techniques which may be further adapted to formal AI initiatives (C12).

*C5: we have **topic teams**, they know data and process, and they say, I want to try this product.*

A company should encourage employees to come up with creative proposal ideas. Innovation labs can be a way to examine the potential of AI to solve client problems outside of traditional product development. It can boost innovation and tech integration within the company as well (C12).

*C12: In the innovation area we see some **initiatives popping up**. There are different sources for that, from our engineers, from IT. Last year we even had a Dragon's Den kind of approach, where people had to pitch their idea, at least give a bit of a hunch on the **business case**.*

For example, people in research and technical marketing in ASML find opportunities in applying computational lithography to optimize mask design and patterning optimization (C13). By combining complementary technology, ASML’s lithography scanners are equipped with enhanced patterning control capability thus being able to extend its services to the semiconductor industry and improve the efficiency of chip manufacturing. Such initiative lands on one of ASML's application businesses by acquiring the company, Brion.

Proposition 2: Bottom-up proposals/Innovation lab positively influences AI organizational readiness.

4.2.2.3 Top management support

For AI initiatives to be successful, top management must provide support for the activities needed by mobilizing resources and promoting innovation culture across the organization to make the general atmosphere more positive around AI (Pumplun et al., 2019) (Jöhnk et al., 2021).

Top management support was mentioned in three interviews. For example, in the first interview, the associated project is an AI-supported cognitive search to capture tribal knowledge. The goal is to develop a smart search engine that can be used to troubleshoot the machine faster and accelerate the learning curve of new employees as ASML is building towards the next generation of photolithography technology with EUV expertise (C1). With more than 100,000 components, such a EUV lithography system is one of the most complex machines ever built (Thoss, 2019, August 29). Such an expert engine can enhance machine diagnostic capability. In this project, top management support is ensured to propel the project forward.

*C1: So from our very senior management level, there were a lot of **buy-ins,** a lot of **attention**, and a lot of **support**.*

In external expert interviews, several interviewees also mentioned the necessity of leadership support and it is nice of senior leaders to gain a profound understanding of AI capability in the semiconductor business world. For example, the second and third experts all mentioned the previous company they worked in have a top-down approach and senior leaders give strategic planning on AI-related activities.

It can be considered as strong top management support if AI deployment is integrated into strategy (Chui et al.,2017). The executive team should be actively involved during strategy development.

*C2: It's really **on the radar of the senior management**, that like this is the improvement point.*

It has been found that projects whether initiated by senior management or not should all experience proof of concept phase. If the project is proved to have added value, a project team can get financial support and other resources from the management board to advancing the project. AI strategy and related initiatives are getting more and more attention on the agenda of senior management in ASML. In addition, top management support is mentioned in industry expert interviews (E3, E8). The decision to incorporate AI into the business is coming from the top-down and the executive team sets up an AI team and expands the team in the deployment.

Proposition 3: Top management support positively influences AI organizational readiness.

4.2.2.4 Business model innovation

There is an increasing trend of service innovation in semiconductors. Equipment makers can provide AI-enabled service to customers with a new business model to capture more value and gain predictable revenue streams (Garand et al.,2020). It can reduce upfront costs for customers in high-capital equipment investment. 9 interviewees mentioned business model innovation.

According to the fourth interviewee, the service business model is already widely adopted in the healthcare and airline industry. Business potential in semiconductors can be huge (C4). He also mentioned that semiconductor equipment companies are in a position to do it as they have the domain knowledge to mine the data. Data alone does not bring value. Thus it makes sense to sell additional services, such as predictive maintenance, to customers.

*C4: We need to sell these **additional services** to the customer. **We are in a position to do it**. If we have this, I think we will also tap the huge business potential of the service sector. The lottery is very big in medical care. This is very big in the airline industry. I think it can also become very big in semiconductors as well.*

What’s more, the sixth interviewee also mentioned service model is a win-win solution for equipment providers and customers (C6). The price of the equipment is high, so being set in a perpetual way is not always the most efficient way for customers as they need to pay too much initially. At the same time, the equipment providers are improving the machines with advanced capabilities for better performance and such added value cannot be charged with the one-time buy contract. Therefore, it makes sense to consider a time-based license model.

*C6: There definitely are some areas from the playground where we're at today. So **setting perpetually** is not always the most efficient… so it's **not a win-win model** really, which is why we're looking at a time-based license type of model.*

Besides, one mentioned a service contract can be made in which customers need to pay a yearly service fee according to a predefined service level agreement.

*C3: I think the **industry is near the tipping point** where indeed they need to i**nnovate in the business model**.*

Regarding the type of business model for equipment vendors, more specifically, it has been found that pure software licenses are difficult to sell as semiconductor companies take their intellectual property and data very seriously. Instead, the software is better to be sold together with hardware for equipment makers and at the same time software should be of high quality with added value for fabs.

*C8: In the future, we want to **charge money on it**, by deferring, as well as **service contracts** with customers if you buy a scanner and you have a service contract that customers have to pay a **yearly fee** for us to serve it.*

Through the interviews, it is revealed that the untapped business potential of data is huge in the semiconductor industry. Innovating in the business model can help the organization win more chances to grasp this opportunity.

Proposition 4: Business model innovation has a positive influence on AI organizational readiness.

4.2.3 Resources

4.2.3.1 Talent

AI deployment requires a broad range of different roles and expertise, including data scientists, machine learning engineers, and business analysts, etc. (Jöhnk et al., 2021).

It can be identified from interviews that there is a lack of personnel with both AI technique and semiconductor background (C9). When a company does not have the talents to build AI capability, it turns to a third party for help which is costly and not good for long-term development.

Three interviewees mentioned the importance of talents for AI organizational readiness. Data scientists, especially with semiconductor background knowledge are difficult to get. The ninth interviewee from Brion mentioned that it is sort of a niche that people with data science backgrounds are not specifically for the kind of things that Brion does as there is plenty of machine learning. Brion is specialized in optical proximity correction (OPC) technique which is commonly used for compensating for image errors caused by diffraction or process variations in photolithography. The following quote illustrates this situation.

C9: And so if we get a candidate, either we have to find a candidate who already has experienced an OPC and might be a good candidate for coming up to speed in machine learning, or we have to find look for candidates who have a background in machine learning, not exactly our background in machine learning, which is unfortunate but that's the way it is. All EDA has this problem.

What’s more, in industry expert interviews, several mentioned hiring enough AI talents is important for organizational readiness (E5, E6). And they are hiring more and more people to work on such projects (E3). Companies need to have a certain number of talents otherwise it would be difficult to obtain a considerable benefit and get the critical mass (E7).

*E5: We want to start **hiring the expertise** in the organization and have them start sorting out and finding these **needles in the haystack**.*

Proposition 5: Hiring more talents with both AI and semiconductor expertise positively influences AI organizational readiness.

4.2.3.2 Financial budget

Financial budgets refer to the financial resources that organizations budget for implementing AI (Pumplun et al., 2019). It has been found in an expert interview that adopting AI requires adjusting AI systems towards a unique semiconductor manufacturing environment, which is time-consuming and costly (E1). To tailor assets to the particular context and data, AI-based systems require significant investments (Jöhnk et al., 2021). By strategically allocating financial budgets for AI adoption, initial obstacles and uncertainties can be overcome. Six interviewees mentioned the budget and example quotes are below. According to interviewees, if a project is initiated from top-down, the budget is sufficient enough to support the development. If it is a bottom-up process, the project team needs to prove the value of the project. Once it is clear, a budget will come to support further development.

C1: As said, because of the senior management and data and the importance, we always got a sufficient budget to proceed.

C4: In the beginning, it was a challenge to prove. But once we have proven, we have the budget.

AI projects do require a budget to cover all expenses associated with technology implementation, operation, and management, which is the basis for incorporating AI into a business.

Proposition 6: Sufficient financial budget positively influences AI organizational readiness.

4.2.3.3 IT infrastructure

A company's ultimate success with AI will likely depend on how suitable its environment is for such powerful applications. Data storage and workloads are high when deploying AI. IT infrastructure with sufficient compute resources, including CPUs and GPUs, and the ability to scale storage as the volume of data grows can enable AI-related activities and AI integration. (Violino, 2021 May 24).

All 14 interviewees mentioned IT infrastructure as an important readiness factor.

One mentioned cloud platforms are in a much higher maturity state at the moment than an on-premise central data lake. Going to the cloud can help boost building data science products much faster (C3).

Despite cloud computing's ascendance as a tool for data-intensive AI workloads, businesses need on-premises resources when they need low latency, data security, or cost-effectiveness (C12). Especially in semiconductors, companies are very cautious about data sharing and intellectual property, thus adopting a restrictive cloud approach.

The ninth interviewee mentioned they are actively looking at GPU support which is requested by customers (C9). But they don’t use the cloud as most of their customers don't use the cloud right now. The twelfth also mentioned that there is a quite restrictive approach to the cloud for both equipment providers and foundries especially for some sensitive product data that cannot be shared into the cloud at the moment. It is a matter of time to shift towards the cloud (C12).

Additionally, hybrid cloud architectures for AI scaling have also gained a lot of attention and if a company needs an AI system for real-time analysis, edge computing should be in place to support it (C6). The response time can be shortened by a larger server with more power that can take care of multiple machines at a client site. As a consequence, you need to have things close to you to get quick access to data and have faster response times, then rely on cloud services for products with low computational requirements.

C12: A larger server with more computing power that can manage multiple machines at a customer site.

But pushing this technology into the customer's fab instead of through Veldhoven infrastructure is more difficult, which requires greater collaboration with the customer (C6). The sixth interviewee mentioned the importance of hybrid computing infrastructure.

C6: So the combination of both in hybrid computing is the most efficient. We are missing the edge part of computing, meaning the computer in the fab.

Proposition 7: Hybrid cloud infrastructure positively influences AI organizational readiness.

4.2.3.4 Competence center

A variety of stakeholders might be involved in AI implementations in organizations (Alami et al., 2020). There may also be organizational silos among different AI-related projects that hinder knowledge sharing on AI know-how. It has been found in the case study that the establishment of an AI Competence Center can optimize the development of AI capability and operational efficiency by centralizing AI expertise.

The competence group is mentioned by 8 interviewees. AI competence center is necessary to better organize different projects and promote knowledge sharing so that a company can build AI capability faster and centralize the skillset to move forward (C4). With stronger AI capability, an organization can maintain the solutions by themselves and keep IP in-house. Companies no longer need to rely on third-party which makes them more flexible in the future (C1, C14).

The first interviewee believes that in-house capability should be there eventually which can make the company more flexible to have new developments and maintain the solutions by the company itself (C1). The sixth interviewee mentioned a unified company-level data strategy is beneficial in the long term but it takes time to build a really good ASML level strategy(C6).

One of the ways a company can do in order to benefit more from AI, in the long run, is to build an organization like a competence center for an increased level of expertise. The sixth interviewee mentioned:

C6: It can be a good thing to have an organization that is grouping the D&E, the research, and development into a group focused on AI in order to increase expertise.

So it is important that companies have competence centers that can help them move to a roadmap approach from a top-down perspective, giving them a clear vision of how the data and AI functions within the organization. On the other hand, one should also realize that it takes time to learn about AI and mature in the development of data-driven products, as it takes considerable time to gain experience.

Proposition 8: Building a competence group to centralize AI skillset positively influences AI organizational readiness.

4.2.4 Process

4.2.4.1 Multidisciplinary team/Collaboration

The development of AI applications is a multidisciplinary effort and relies on integrating different perspectives, i.e. domain knowledge, data, and IT (Piorkowski et al., 2021). A multidisciplinary team or collaboration across different departments enables employees to work together and combine different skills to lead a successful project (Jöhnk et al., 2021).

12 interviewees stressed the importance of a multidisciplinary team in the case study.

In a multidisciplinary team, there are software engineers, data engineers, infrastructure engineers, and machine learning engineers as well as domain experts in the team to develop the solution (C8). A project manager oversees the whole picture and is responsible for everything.

C8: So this data scientist, data engineer, domain expert, and software component is the flesh that you need to combine.

C4: let's say, it's not only a machine learning solution, it is about the entire collaboration between different teams. And also the ML machine learning operations, data on production operation.

For the deployment and operation of the product, engineers from customer service and the local team are involved to ensure it works at customers' sites (C12).

C12: We work with a lot of other departments. It's also a lot of collaboration between the factory and the service engineers. It's both IT as well as business we have quite a lot of different collaborations.

The effectiveness of multidisciplinary teams or cross-functional collaboration leads to employees being able to work together, utilize their different skills, and enforce expertise (C14).

C14: We can enforce expertise by more collaboration ways of working.

Proposition 9: Multidisciplinary team and cross-functional collaboration positively influence AI organizational readiness.

4.2.4.2 Agile way of working

In the area of AI and advanced analytics, where poorly defined solutions are best iterated through fast iterations, Agile is a natural fit (Lee et al., 2020). Utilizing agile techniques positions companies to reap some substantial rewards in scaling AI: faster time-to-market, the ability to fail fast and re-think, and enhanced collaboration across departments. (Lee et al., 2020) In the context of AI, a transition to agile work forms becomes necessary (Pumplun et al., 2019).

9 out of 14 respondents mentioned teams are built in an agile manner.

C4: We do an agile way of working. It's one of the key things.

Three roles are involved in scrum: the product owner, the scrum master, and the development team (C1). ASML now is in the middle of agile transformation with the moment with the Scaled agile framework (SAFe). As a set of organization and workflow patterns, the Scaled Agile framework is designed to help organizations scale lean and agile practices (Knaster, 2021).

C1: Within we're trying to work according to the SAFe.

The advantage of agile is that people from other teams or departments can talk with the product owner which is a very flexible and transparent way of working.

C2: I do see we are adapting to a more agile way of working. And that's really good that we can actually talk to a product owner of this product architect, also it safe and more flexible.

But at the same time, one mentioned that agile is not a "one-for-all" solution. The effectiveness of the agile technique should be further examined when the project is in the phase of a proof of concept where real innovation comes. Agile works well when the goal or product requirements are clear (C10).

C10: I'm not sure that SAFe or agile is the best way to innovate things. safe or agile is for integrating and implementing, if you know what to do, then then it works perfectly. If you really have to innovate, I'm not sure that is the best way of organizing.

Proposition 10: Agile way of working (e.g. SAFe) with a clear goal positively influences AI organizational readiness.

4.2.4.3 Employee Training

The purpose of employee training programs is to equip the workforce with the necessary AI skills to become proficient in the use of intelligent machines. It is only when both the company and employees have an opportunity to meet their common aspirations in the workplace that it becomes feasible to make the transition to an AI-enabled environment. (Jaiswal et al., 2021)

6 interviewees mentioned it in the case study interviews.

Employees need to be trained to better use AI models to accelerate the model deployment in terms of projects with customers involved (C4). Regarding internal projects, essential training should be provided to related stakeholders to manage the change and create a data culture (C5).

C4: So in our team, we have end-to-end people, not only helping the models but also deployment. In addition to that, indeed, there is some planning to get up there at ASML to help boost some of these deployments.

C5: Training can be the official training from the tool itself but also can be the trainee by somebody in our team to our internal stakeholders.

Furthermore, when new hires are not equipped with industry background knowledge or AI techniques as there is a shortage of skilled AI and domain experts, essential training can help them adapt to the new role quickly and contribute to the organization (C9).

C9: And so new hires go through a series of basic training and OPC and then advanced training

The company needs to invest in employee training to upgrade the skills and improve performance. This would help prepare employees for higher duties which means increased efficiency and therefore increased business growth in the long run (Howe, 2018).

Proposition 11: Upskilling the workforce positively influences AI organizational readiness.

4.2.4.4 Business process standardization

To make sense of data, it must be aligned with company processes (Ribeiro, 2021). It has been mentioned that some AI applications need structural changes in the business process within the organizations (C5).

C5: If the predictive model works. But it's requiring a structural change in their process and some changes in their process. Then, we will face some challenges.

Without a standard business process, working efficiency can be a problem. According to the eighth interviewee, some use Excel and some use the more advanced tool to collect data. Data portfolio is not easy to be managed in this way (C8). As a consequence, data scientists need to spend extra time to collect those numbers which makes it hard to focus on data analysis. So in the future, a lot of legacies should be fixed to automate the processes and make sure it is up to date.

C8: For me as a data scientist I think I'm skipping a couple of steps in maturity I'm already deploying AI to the field, but the back end, the rest of the organization, the processes behind it are still working with excel and are not automated at all.

Besides, a standard should be made to ensure a smooth business process flow with **task priority** to prevent the chaotic. The eighth interviewee also mentioned there's a lot of different projects that all are fighting for the same memory and CPUs and the IT department needs to make this decision on which project to serve first (C8). However, it is not reasonable to prioritize the tasks by IT and it should be done through careful analysis considering business importance level.

In order to have fewer craps in the business process, a good taxonomy is a way to help manage the complexity (C11). Related standards need to be defined. The eleventh interviewee mentioned the necessity to create a good taxonomy to deal with process craps.

C11: if we create a good taxonomy if we've created good content lifecycle management rules. At least we stay, we know that the content is fresher and that the AI is at least tried to process less crap.

Proposition 12: Well-defined business process (tool, task priority, taxonomy) positively influences AI organizational readiness.

4.2.5 Data

4.2.5.1 Data availability

Data availability refers to the amount and types of data that are available, which can be used in the training of artificial intelligence models and for the prediction of future events (Chui et al., 2018).

9 interviewees mentioned data availability issues and considered it as an important readiness factor.

According to most interviewees, companies have a conservative attitude towards data sharing in semiconductors. Protecting the intellectual property of semiconductor companies is one of the most important things that they can do (Garand, 2020). Otherwise, they may lose their market. This is a business limitation for the whole semiconductor ecosystem.

C9: We do face data availability problems. It's a general problem with the entire industry, And that's just the nature of the game because again if a foundry ever had a data breach. They would potentially go out of business immediately.

Such a conservative approach leads to limited data sets for AI development which is one of the biggest concerns for the company (C8). Many mentioned the data availability challenge in development.

C8: Now how much data is there available. This for me is my biggest worry. We have the sensors, but the data is still on the scanner, it's not transported to Veldhoven.

C6: The problem is we are doing with developing tools on a limited set of data because the data is not in ASML, the data is in customers'.

It is imperative to create a transparent policy and agreement as mentioned by the tenth interviewee so that semiconductor companies can be comfortable with the sharing of end-to-end data across the entire ecosystem, to manage the data access appropriately and reach a win-win solution (C10).

C10: there should be a ***transparent policy on the issue and agreement with our customers*** *before we can use data, let's say that handles all the data with the proper access management so that everybody no longer needs to* ***hop around all the data****.*

In addition, it is discovered that both the availability of data and the quality of data are linked since both require constant improvement inconsistency with model development standards (C4).

C4: So we need to see how we can consistently improve the quality and data availability.

Moreover, new methods are being developed for constructing models with limited data sets, such as Variational Bayesian methods, which to some extent solve the lack of data issue (C13).

C13: The idea is variational Bayes. So you don't need all the data, you just need some of it to model the distribution then you can generate more work. I'm very excited. We can use it a lot because we are data-limited.

Proposition 13: The lack of data negatively influences AI organizational readiness and a transparent policy or agreement with customer positively influences AI organizational readiness.

4.2.5.2 Data governance

The term data governance can be defined as an overall framework dealing with the management of data and a company's control over the quality of the data with consistency, accuracy, accessibility, completeness, and the risk involved with protecting privacy, security, and compliance. (Cohen, 2016) Data need to be carefully governed as part of establishing data readiness for training and inference to maximize the vast potential of big data (C13).

C13: Make sure the data is governed correctly.

10 out of 14 interviewees consider data governance as an important AI organizational readiness factor. To ensure the high-quality input for AI models, there should be a good process for checking the quality of the data you collect, getting the right data from the system (C2). Data governance also helps the company utilize data strategically and improve product quality to meet customers' expectations (C7).

C2: Making sure we at ASML strategically, understand what is the kind of data we want to share, and what is the kind of data we want to provide better quality.

C7: So we need to find our perspective in the data quality features, the algorithm. So we need to find a way to enhance the quality and the precision to be able to reach the customer standard

It is important to have clear data ownership to create a better data pipeline and have unified data formats (C1). As a result, data can be managed more efficiently due to less time on data preparation. The business benefit will come downstream in deployment and maintenance (C12).

C1: Because nobody reviews it, then it takes you much more time to establish that similar pipeline and set up.

C12: So in the design area you need to prepare your data much better so that it can be of business benefit more downstream in manufacturing or service.

Consistent and trustworthy data can be ensured by data governance, so they do not get mishandled.

Proposition 14: Data governance positively influences AI organizational readiness.

4.2.5.3 Data platform

An enterprise data platform enables data to be managed, accessed, and delivered to targeted users to build data applications for strategic business purposes (Booth et al., 2018).

Seven mentioned the data platform in the case study.

C4:Data center platforms are key for innovation or let's say they are key to land our data sets.

Data-driven products cannot be built when the development tools and data are dispersed throughout the organization. Moreover, a data platform will be vital to scaling up the projects as the applications mature (C4).

C8: I think there's a big room for improvement in the strategy, so I need a platform, I need tools to augment those models, and I have to have to redesign them and pull them myself.

With a proper data platform, the complexities of developing enterprise AI applications can be reduced and the AI development cycle can be accelerated to achieve fast delivery (C3).

C3: I invest first in making sure we go to the clouds to have a very fast release cycle. And then you can prove that AI works. But if you focus first on the algorithm, and forget about all the rest, you just will not be successful.

Proposition 15: Data platform positively influences AI organizational readiness.

4.2.6 AI model

4.2.6.1 Explainable AI with domain expert

Explainable AI is artificial intelligence in which the results of the solution can be understood by humans. It contrasts with the concept of the "black box" in machine learning (Ankarstad, 2020). Explainable AI is essential as you do need to understand what is happening inside the model. If not, it is hard to improve it and troubleshoot it when things go wrong (C3). To successfully implement AI, a domain expert that provides domain-specific knowledge such as dataset sources, usability, and recommendations quality is a key element. (Elias, 2020)

12 interviewees think of it as an essential factor.

C13: So I do want to understand the processes and how physically these things work. I do think that helps in designing what the model should look like.

The best use of artificial intelligence is in conjunction with human interaction (Miller, 2019). Achieving AI's full potential requires a combination of better process steering, technical upgrades to address the system's identified issues and opportunities, and improved performance management. Neither can be completed without the participation of domain experts in the process.

C4: At the same time combine the domain knowledge in a very nice way. So that the algorithm which you've created can work for other questions as well. So we have some IP here.

Domain experts that have a fundamental understanding of the model is a key differentiator in AI game (C8). They understand the concept of creating machine learning models with specific features.

C8: Success is when we have domain experts from the function clusters that know all about the part that we want to model.

However, domain experts are scarce and domain knowledge relies a lot on experienced people (C2). Building the expert system is a way to improve the situation.

C2: And those people are very rare, or the combination of these activities happens very seldom. We rely a lot on senior people.

Overall, prediction models need domain experts to provide context for the data and help determine which results are useful for practice.

Proposition 16: Domain experts that have a deep understanding of the application area positively influence AI organizational readiness.

4.2.6.2 Context-aware AI modeling

Contextual AI emphasizes a human-centric approach to AI. Ideally, an AI system should be adaptable to a variety of situations or environments so that it meets the expectations of the user (Brdiczka, 2019). An AI application that is context-aware attempts to understand the user's situation and be able to interact and explain itself effectively (C4).

C4: You need the context information, like what happened to the customers. Your models should be sharp enough to do to deal with these challenges.

Generally, it is more cost-effective to train a general and versatile machine learning model than to train several specialized machine learning models for different operating situations as mentioned by C10:

C10: We hope that it's more generic than just for one customer.

Six interviewees mentioned the importance of context-aware modeling.

On the one hand, development teams need to make sure that the machine learning algorithm, which you create for a product will also work for the new version after the product itself has updates. On the other hand, the self-learning model developed by the providers may need optimization after it is deployed at the customers' sites. A feedback loop between two stakeholders should be in place. This feedback is used to train and tune the model so that it will eventually adapt to the specific context of a particular customer and be able to learn and improve their performance over time (Donker, 2021).

C13: We design it based on, maybe some mass balance constraints, some optical imaging type of constraints, we take those into mind we are context-aware. It's not just, yeah, here's some data regress and goes.

A lot of parameters should be set up to increase the flexibility of the adjustments for a model development team. The machines can then be finetuned so that the customers' manufacturing processes can be optimized (C7).

C7: So we can have a lot of parameters, we can tune to make it more specifically for the

specific customer.

Proposition 17: Context-aware AI modeling that can make the system adaptable to a variety of situations positively influences AI organizational readiness.

4.2.6.3 Model operation

In the context of model operations, this refers to integrating AI models and algorithms into production applications, as well as how the models behave and evolve, and what processes are used to build, confirm and consume these models (Hummer et al., 2019).

6 interviewees mentioned it in the case study.

Building the model is the easiest part compared to making that model going daily that can generate outputs and share the results with all the local teams. The latter one needs a lot of software which is quite complex (C8).

C8: We have the competence to build these AI models, but deploying and automating them is quite challenging.

One mentioned that they have two different environments which are model development environment and production environment (C7). Thus for the final product, it's a standalone software that aims to be deployed at customer sites.

C7: So our development environment is on GCP, google platform. And for the final product, it's a standalone software that aims to be deployed at customer sites.

To make the model work and scale, customers need to store as much historical data as possible so that the tool can start and keep learning faster (C3). It is found that a big challenge is to troubleshoot the tool as it is in the fab and equipment providers cannot access the data. Instead, a diagnostic report is there to give clues on the issues and how to improve with further steps (C7). Fabs very often don't give you enough information to be able to reproduce the problem which adds difficulty in model operation (C9).

Additionally, a variability issue exists as a result of the different equipment used in high-volume manufacturing. It establishes stricter requirements for the development of models. It is good to build the system having the state of the system in mind as in the development (C13).

C13: You can use that same model but you have an estimate of where you are in the space that you're operating in. So I always try to build these things with the concept of having a state of the system.

In summary, model operations are focused primarily on the life cycle management of a wide range of operationalized AI models. The idea is to integrate AI models in production applications, to consider properties that determine how the models behave and evolve, as well as the processes used to build, test, and evaluate the models.

Proposition 18: Model operation positively influences AI organizational readiness.

4.2.7 External business environment

4.2.7.1 Peer companies/competitors/software vendors

The increasing competitive pressure leads companies to utilize AI to gain a competitive advantage (Alsheibani et al., 2018) (Pumplun et al., 2019).

Healthy competition can make a company develop a better product (Westbrook, 2018). And especially in the EDA sector of the semiconductor value chain, ML is embraced by most companies to gain a competitive advantage.

*C9: **Every EDA company is pursuing**, and I believe every EDA company has some sort of product that's associated with machine learning right now.*

*C10: And now they feel the pressure, and they are starting to improve themselves so that you could easily consider that **a healthy competition** and say they are challenged to make their product also better.*

It is essential to keep track of what your competitors are doing and to stay competitive.

At the same time, a company can learn from peers. It is beneficial to take away their best practices and share your experience (C5). In addition, software vendors see AI as an opportunity and are pushing technology (C12).

C5: We also learn from our peer companies.

C12: we also get, let's say, technology push from vendors that we work with either software vendors or consulting firms that think there's an opportunity there.

Proposition 19: Peer companies/competitors/software vendors positively influence AI organizational readiness.

4.2.7.2 Customer demand

In making a decision to introduce artificial intelligence into a business, companies must also consider the knowledge and acceptance of their customer base (Pumplun et al., 2019).

There is a demand from the customer to develop a predictive AI model for equipment vendors (C8).

*C8: We started predictive maintenance one and a half years ago, there was a **request from a customer** as well. Samsung, Intel, they're very interested in predictive methods.*

The demand from customers can make equipment providers engage more in AI development. In semiconductors, fabs have rich data of manufacturing process but they lack in-depth knowledge on tools that drives the collaboration between the company and the customer (C6).

C6: Intel TSMC Samsung Hynix and they are asking for our help because ***they know that they cannot go so far if they don't have our knowledge****.*

Moreover, faster time to market for foundries in a sense strengthen their demand for AI. So there is a trade-off between the quality and the time to deliver the systems (C3). AI is typically very good at machine behavior optimization as the machine cannot be not fully controlled by equipment providers in a customer site in the current business environment (C3).

Proposition 20: Demanding customer positively influences AI organizational readiness and strengthen the relationship between foundries and equipment vendors.

4.3Conceptual framework

4.3.1 Proposed AI organizational readiness framework

The proposed conceptual framework is developed through case study interviews. Twenty factors within six dimensions are identified in AI organizational readiness framework which is shown in Figure 13 below. Blue ones (No.1, 3, 5, 6, 7, 9, 11, 13, 19, 20) are identified from the literature review (Alsheibani et al., 2018; Pumplun et al., 2019; Alami et al., 2020; Jöhnk et al., 2021) and also are supported in the case study interviews. More detailed information about typical readiness factors in existing literature can be found in Table 1 in section 2.1.3. Green ones (No.2, 4, 8, 10, 12, 14, 15, 16, 17, 18) are newly identified from case study interviews. The distribution of 20 influencing factors mentioned in the interviews can be viewed in Table 6 in section 4.3.1. The characteristics of all readiness factors can be found in Table 7 in section 4.3.2.

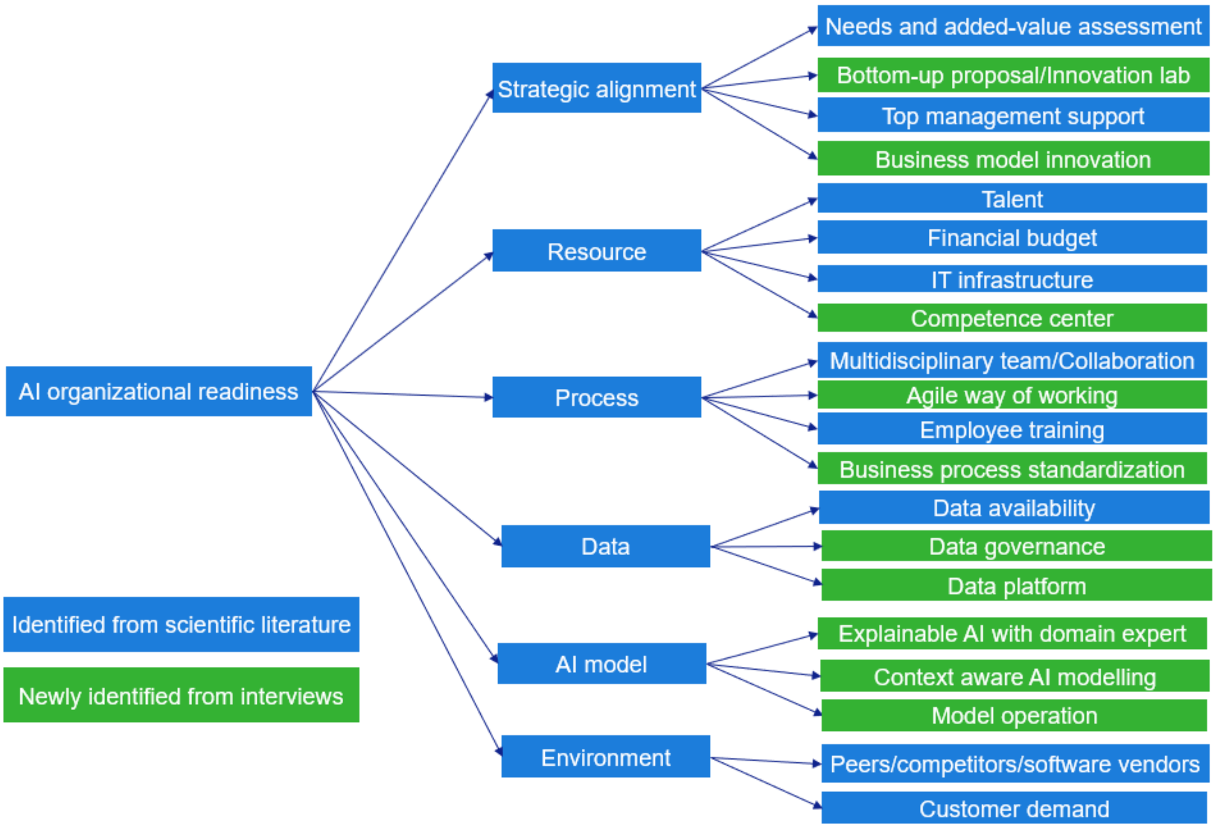

Figure 13 Proposed AI organizational readiness framework

In the **strategic alignment** dimension, there are four influencing factors which are 1) needs and added-value assessment, 2) bottom-up proposal/innovation lab, 3) top management support, 4) business model innovation. Needs and added-value assessment is derived from Alami et al. (2020) in which this factor is proposed aiming to avoid the negative effects AI may bring to the organization and Jöhnk et al. (2021) in which "AI-business potentials" is proposed to make sure AI is deployed with a clear business case (the need to use AI and associated business value). From case study interviews, I found that AI should be viewed as a tool with a clear purpose rather than an independent entity. Assessment of AI needs and added value is essential to ensure AI is a good fit for the business case in the organization. Bottom-up proposal/Innovation lab is a new factor identified from case study interviews. It is a good way to explore the potential of AI to solve problems and can improve innovation and technology integration within an organization. Alsheibani et al. (2018), Pumplun et al. (2019), and Jöhnk et al. (2021) all mention "top management support" as a factor that can positively influence AI readiness as a top leader can coordinate resources to facilitate AI deployment. In this research, I have also found that the organization adopts a top-down approach to set up a project team and senior leaders give strategic planning on AI-related activities. Business model innovation is a new factor and I find through the research there is an increasing trend of servitization in semiconductors so that equipment makers can provide AI-enabled service to customers with a new business model to capture more value and gain predictable revenue streams.

In the **resource** dimension, 5) talent, 6) financial budget, 7) IT infrastructure, 8) competence center are identified as AI organizational readiness factors. Alsheibani et al. (2018) propose "human, enterprise and technology resources" are important resources to adopt an innovation. Pumplun et al. (2019) propose three pillars in resources that are budget, employees, and data. Jöhnk et al. (2021) list three factors in the resources dimension which are financial budget, personnel, and IT infrastructure. In this research, talent, financial budget, and IT infrastructure are proved as well. Talent is crucial as there are many different roles and levels of expertise required to deploy AI, including data scientists, machine learning engineers, domain experts, etc. AI-based systems require significant investments so the financial budget should be in place to support the project. Regarding IT infrastructure, I find AI success relies heavily on how well a company can support robust applications within its IT infrastructure due to high data storage requirements and workloads. Additionally, hybrid cloud architectures for AI scaling have also gained a lot of attention. Edge computing is needed if a company needed an AI system to do the real-time analysis so that having computing power in the fab and ASML site are both important. Competence center is a new factor identified through the case study which can help centralize AI expertise and promote knowledge sharing on AI best practices.

In the **process** dimension, there are four readiness factors: 9) multidisciplinary team/collaboration, 10) agile way of working, 11) employee training, 12) business process standardization. Jöhnk et al. (2021) propose "collaborative work" to combine different skillsets of employees. This study also finds AI development is a "multidisciplinary" activity integrating data, domain knowledge, and information technology perspectives. Working across departments or in multidisciplinary teams allows employees to collaborate and pool resources to produce effective projects. The agile way of working is a new factor added to the framework. Using agile approaches for developing AI can result in faster time-to-market due to short iterations, and improved communication across departments. Considering the situation of global chip shortage, it makes sense to improve manufacturing efficiency with an agile way of working. Alami et al. (2020) think "appropriate training" may be involved in establishing organizational readiness and similarly Jöhnk et al. (2021) mention "AI awareness" and "upskilling" that aim to provide employees with sufficient AI knowledge and skills. This study also finds "employee training" important to equip the workforce with the necessary AI skills. Business process standardization is a newly found factor as the deployment of AI brings changes in business processes that should be improved towards data-driven and more well-defined to prevent chaos.

Regarding **data** dimension, 13) data availability, 14) data governance, 15) data platform are included. Data availability is mentioned by Pumplun et al. (2019) and Jöhnk et al. (2021). I find in the research that semiconductor companies have conservative attitudes towards data sharing which will negatively influence AI readiness as the training of artificial intelligence models and for the prediction of future events needs a sufficient amount and types of data. Data governance is derived from "data quality" proposed by Jöhnk et al. (2021) as data governance incorporates a wide range of data management areas such as data ownership, data cleaning. Data governance is considered an important factor according to interviewees in the case study, for example, "Make sure the data is governed correctly" mentioned by C13. The data platform is newly identified in the research. By managing, interacting with, and delivering data to targeted users, the data platform enables data-driven applications for strategic business purposes to be developed.

In the **AI model** cluster, 3 new readiness factors are identified, 16) explainable AI with domain experts, 17) context-aware modeling, 18) model operation. The AI model should be adapted to a certain domain in the industry with deep domain knowledge to build more explainable AI systems that can enhance customers' trust. To develop a more generic AI model that can be applied to different operating situations with flexibility, AI model development should be context-aware. Moreover, model operation capability is necessary to build to keep an eye on the whole process and lifecycle management of the model.

In the **external business environment**, there are two AI organizational readiness factors which are 19) peers, competitors, and software vendors and 20) customer demand. Alsheibani et al. (2018) propose "competitive pressure" can motivate the organization to bring in innovation. In this research, I find not only competitors but also peers and software vendors can have a positive influence on AI readiness. Regarding "customer readiness", Pumplun et al. (2019) propose “demanding customers will nudge the companies to design individualized, intelligent products” while Jöhnk et al. (2021) propose “organizations need to prepare customers by forming adequate expectations”. In this research, it has also been found that customer demand accelerates the development of AI solutions for the company.

4.3.2 Discussions

The developed framework conceptualizes 20 AI readiness factors from an organizational perspective. Table 8 below shows 20 propositions on AI readiness in semiconductor organizations (13-18 are AI-specific factors and propositions). General factors and AI-specific factors as well as the use and generalizability of the framework are discussed in the following subsections.

Table 8 Overview of 20 propositions on AI readiness in semiconductor organizations (13-18 are AI-specific factors and propositions)

No.	Readiness Factor	Proposition
1	Assessment of needs and added value	Assessment of AI needs and added value positively influences AI organizational readiness.
2	Bottom-up proposal/Innovation labs	Bottom-up proposals/Innovation lab positively influences AI organizational readiness.
3	Top management support	Top management support positively influences AI organizational readiness.
4	Business model innovation	Business model innovation has a positive influence on AI organizational readiness.
5	Talent	Hiring talents with AI and semiconductor expertise positively influence AI organizational readiness.
6	Financial budget	A sufficient financial budget positively influences AI organizational readiness.
7	IT infrastructure	Hybrid cloud infrastructure positively influences AI organizational readiness.
8	Competence group	Building a competence group to centralize AI skillsets positively influences AI organizational readiness.
9	Multidisciplinary team/Collaboration	Multidisciplinary team and cross-functional collaboration positively influence AI organizational readiness.
10	Agile way of working	Agile way of working (e.g. SAFe) with a clear goal positively influences AI organizational readiness.
11	Employee Training	Upskilling the workforce positively influences AI organizational readiness.
12	Business process standardization	Well-defined business process (tool, task priority, taxonomy) positively influences AI organizational readiness.
13	*Data availability*	*The lack of data negatively influences AI organizational readiness and a transparent policy or agreement with customer positively influences AI organizational readiness.*
14	*Data governance*	*Data governance positively influences AI organizational readiness.*
15	*Data platform*	*Data platform positively influences AI organizational readiness.*
16	*Explainable AI with domain expert*	*Domain experts that have a deep understanding of the application area positively influence AI organizational readiness.*
17	*Context-aware AI modeling*	*Context-aware AI modeling that can make the system adaptable to a variety of situations positively influences AI organizational readiness.*
18	*Model operation*	*Model operation positively influences AI organizational readiness.*
19	Peers/competitors/software vendors	Peer companies/competitors/software vendors positively influence AI organizational readiness.
20	Customer demand	Demanding customer positively influences AI organizational readiness and strengthen the relationship between foundries and equipment vendors.

4.3.2.1 AI-specific organizational readiness factors

In this study, AI-specific factors refer to readiness factors in data and AI model dimensions which can be seen in Table 8 as blue ones. This study identifies new AI-specific readiness factors that result from the unique features of AI applications in the semiconductor industry, such as **explainable AI with domain experts**, **context-aware modeling**, **model operation**, **data availability**, **data governance, data platform**.

The data availability challenge is stressed in many interviews in this research as well as in previous literature (Pumplun et al., 2019) (Jöhnk et al., 2021). The complexity of the semiconductor manufacturing process requires AI models with high accuracy and adds difficulty in implementation (Lapedus, 2021). Data governance can help an organization achieve business value and accelerate an AI transformation by better managing data usability, integrity, and security (Chan, 2019). It is important to have a data platform that serves as a strong tool to shorten the development cycles and bring AI applications earlier to the market (E3). Enterprises need to have a data platform that helps build AI applications for strategic business purposes (Booth et al., 2018).

The use of technology alone is not sufficient to help businesses meet their challenges. It goes beyond AI expertise. It is always essential to gain a deep understanding of the problem space while also being familiar with its key data. (Zakur, 2021) Companies need domain expertise to make AI models more explainable which is beneficial for troubleshooting. At the same time, explainable AI application makes it easier to gain trust from customers (C3). AI modeling that is context-aware can enable the system to adapt to a variety of situations (Brdiczka, 2019). Semiconductor manufacturing requires a high level of accuracy and is sensitive to small variations (Esmaeilian et al., 2016). Thus, it is important that the model can deal with those minor changes. The model operation focuses on the life cycle of the AI model from development to deployment (Hummer et al., 2019). The model after being tested in a lab environment is deployed at a customer's site. Thus, it requires the model itself to have self-learning ability but also providers are responsible for the operationalization of the model, for example, upgrading, troubleshooting, etc. (C3).

4.3.2.2 General AI organizational readiness factors

Multidisciplinary teams and collaboration among different departments are important for model development and implementation. Software engineers, data engineers, infrastructure engineers, and machine learning engineers as well as domain experts should all be involved (C8). Additionally, after deployment to the customer site, customer Support employees should be trained in troubleshooting the AI product (C7).

At the same time, a robust IT infrastructure is required to handle computationally intensive workloads with a shift towards the cloud and it is ideal to have a hybrid computing environment that combines on-premise data centers and public cloud. Moreover, edge computing deployed at customers' sites would be beneficial in the future to provide real-time analysis (C6). However, it is still a long way to go as semiconductor companies have a restrictive data sharing approach to protect their IP.

Furthermore, value assessment (business case) should be considered carefully before the start of the AI project with a clear business case in mind (Alami et al., 2020) (Jöhnk et al.,2021). Innovation labs can be in a good way to bring up new ideas that can be further adapted to a valuable business case (C12). And the business model is worth to be explored as the service model is untapped but with huge business potential in the semiconductor industry (Garand et al., 2020)

To scale the business up, it is necessary to adopt an agile way of working. (Lee et al., 2020). Providing employee training is necessary to upskilling the workforce and make an easier transition to an AI-enabled environment in the company (Jaiswal et al., 2021).

Fundamental readiness factors such as top management support, talent, financial budget are less stressed in the case study interviews as they are almost universally valid, and case study interviews focus more on new factors that are of importance in AI organizational readiness.

4.3.2.3 Reflection on the use of the framework

Companies should have a certain degree of AI readiness to pursue and reap the benefits of AI initiatives (Alsheibani et al., 2018).

This study conceptualizes 20 factors in total that influence AI organizational readiness. In this study, AI organizational readiness is defined as “the extent to which an organization has the ability to reap the benefits of AI". It should be considered as a dynamic and constant issue for companies rather than a one-time consideration since readiness specifications may differ in accordance with the intended application of AI and the experience gained through previous cycles (Jöhnk et al.,2021).

The proposed AI organizational readiness framework can serve as a readiness assessment for companies that target AI. Inspired by the method "Technology readiness level (TRL)" that can be used to assess the maturity level of a certain technology (Mankins, 2015), I distinguish four levels of AI organizational readiness in this study which are: No experience, AI starter, AI-ready, AI advanced, reflecting the gradually increasing maturity. The description of each level can be found in table 9 below. Consequently, enterprises could embark on a journey to enhance their AI capabilities by leveraging appropriate programs.

Table 9 Level of AI organizational readiness and description

Level of AI organizational readiness	Description	Average score
No experience	The organization has no experience in AI and intends to use AI in the business. The organization does not have clear use cases and is waiting until the benefits are proven across the industry.	$0 \leqslant x < 1$
AI starter	The use cases that need to be solved with AI are identified in the organization. The company starts investing in AI to coordinate necessary resources and has done a few trials to develop the model.	$1 \leqslant x < 3$
AI-ready	The organization is capable of applying the AI model in the business on a small scale and the test results are good enough to scale it up. A concrete deployment plan has been established and communicated across the organization.	$3 \leqslant x < 4$
AI advanced	The organization can successfully integrate the AI model into the business process and operationalize the model on a daily basis. AI expertise is centralized for new use cases in the future.	$4 \leqslant x < 5$

It can be viewed as a tool to assess an organization's AI readiness. More specifically, each factor can be assessed with a score profiling an organization's current AI organizational capability. The scoring description can be seen in Table 10 and a detailed assessment description for each factor can be found in Table 11. An example use of the framework is given in Appendix H which shows the scoring process. Rader charts are made to visualize the strengths and weaknesses of an organization's AI readiness.

After the assessment, the organization can analyze the gaps between the current situation and the desired outcome. Thus, it can provide guidance for decision-makers, managers, and project teams for faster and better development and deployment of AI.

Table 10 Scoring description of AI organizational readiness factor

Score	Description
0	The element does not exist or completely is not taken into consideration in the organization.
1	The element exists in the organization but cannot support the business.
2	The element can meet the business' basic requirements (<50%) but there still are some challenges in the organization.
3	The element can meet the majority of needs (50%~75%) and there are some small problems that need to be fixed.
4	The element can meet almost all the needs (75%~100%) for the targeted AI application in the organization.
5	The element is well-applied in the organization and is routinely checked for continuous improvement.

Table 11 AI organizational readiness assessment

Dimension	No.	Readiness factor	Assessment	Score
Strategic alignment	1	Assessment of needs and added value	The organization can identify suitable AI use cases that provide added business value. The organization views AI as a tool to solve problems.	
	2	Bottom-up proposal/Innovation labs	The organization encourages employees to innovate and propose potential improvement points. The innovation lab, hackathon, workshop, etc. are held.	
	3	Top management support	Management support is in place to allocate necessary resources.	
	4	Business model innovation	The organization takes business model design into consideration that best fits the targeted AI application/product.	
Resources	5	Talent	The organization has a certain amount of talents with AI and industry expertise that ensure the model development.	
	6	Financial budget	The budget is sufficient for all kinds of activities around building AI solutions.	
	7	IT infrastructure	The organization has appropriate and adequate IT infrastructure to support the model training and development.	
	8	Competence group	To build in-house AI capability, the organization recognizes the importance of knowledge management to centralize AI skillsets and learn from experience.	
Process	9	Multidisciplinary team/Collaboration	The multidisciplinary team is composed to facilitate AI development. Collaboration across departments can be achieved if necessary.	
	10	Agile way of working	The organization adopts an agile way of working to have fast development cycles.	
	11	Employee Training	The organization provides employee training with necessary AI skills.	
	12	Business process standardization	The organization establishes clear and standardized business processes to avoid redundant work and enable the integration of AI applications.	
Data	13	Data availability	The organization gains an adequate amount of data for the model development.	
	14	Data governance	The organization can ensure the quality, clear ownership, security of the data.	
	15	Data platform	An appropriate data platform is there to reduce the complexity of development.	
AI	16	Domain expertise for explainable AI	The organization has domain experts with a deep understanding of the application to determine the feature of the model and make it more explainable.	
	17	Context-aware AI modeling	The model can adapt to a variety of situations. It has a self-learning ability to work in different contexts and improve its performance over time.	
	18	Model operation	The organization can manage the model throughout its lifecycle in business.	
External environment	19	Peers/competitors/software vendors	The organization learns from its peers, competitors, and other vendors to track the market dynamics in AI applications and keep competitive in the market.	
	20	Customer demand	The organization understands the customer demand and makes improvements.	

4.3.2.4 *Generalizability of the proposed conceptual framework*

This section discusses the generalizability of the proposed AI organizational readiness framework. It reflects on the usefulness of the research, more specifically, whether its findings can be applied to individuals or scenarios that are broader in scope[2].

This qualitative study focuses on AI organizational readiness in the semiconductor industry and data are collected through 8 industry expert interviews and 14 case study interviews in ASML, a leading manufacturer of chip-making equipment. But the proposed conceptual framework can be applied in not only semiconductors but other industries as well. Use cases involved in this study such as predictive maintenance, process control, defect inspection have wider applications in not only semiconductor manufacturing but other industries as well.

First, the concept of predictive maintenance is to utilize artificial intelligence to identify potential problems in the operation and determine when it is time to perform maintenance on equipment. Data is collected over time and an AI-enabled predictive model is created to monitor equipment performance, minimize unscheduled downtime, as well as prevent device failures. The goal is to discover patterns through the model training process, finding relationships between historical data and current readings (Gonfalonieri, 2019). It can be used in railway for health monitoring of point machines, in oil and gas for the optimal lifetime of the system, in the manufacturing industry such as automotive, aerospace, and shipbuilding for various equipment (Mobley, 2002). What's more, it is broadly applicable across the manufacturing sector and is quickly becoming a crucial part of Industry 4.0 (Brzozowska, 2020).

Second, process control is a method of quality control to reduce variations and improve operation efficiency. For example, it has been used for disease management and critical care in healthcare (Thor et al., 2007) and in the food industry for improved process control (Lim et al., 2014). Integrating AI into process control helps in interpreting quality characteristics which can be used to predict the outcome of the quality characteristic and product characteristics ultimately (Zan et al., 2020).

Third, defect inspection enabled by AI-based visual inspection can be used in detecting internal defects of additive manufacturing components in the aerospace and defense industries (Chen et

[2] https://www.hydroassoc.org/research-101-generalizability/

al., 2021). Intelligent defect inspection is crucial in high-value manufacturing such as aerospace, automotive, construction, and medical devices since a defect in a part or component can be disastrous (Infopulse, 2019).

In summary, this study collects qualitative data from case study interviews that involved different AI-related projects. Besides the use cases mentioned above that can be widely used in different manufacturing industries, there are other applications such as AI-based cognitive search to build a smart search engine, knowledge management through natural language processing connecting up-to-date knowledge from various resources, AI in product lifecycle management involved in this research. Such AI applications can be applied in almost any industry. Thus, the proposed conceptual framework regarding AI organizational readiness derived from a variety of AI applications can be applied to other industries to some extent after further examination.

5 Conclusion

In this chapter, the conclusion of the research is discussed. The main findings of the thesis are summarized answering the main research question and sub-questions in section 6.1. Theoretical contributions and practical contributions are provided in section 6.2. The limitations of research and recommendations for future research are discussed in sections 6.3 and 6.4 respectively. At last, personal reflection and the link to MSc. Management of Technology is presented in section 6.5.

5.1Conclusion

To summarize the results above, this qualitative study develops a conceptual framework for AI organizational readiness in semiconductors by conceptualizing empirical readiness factors in semiconductor organizations. The proposed framework can be found in section 4.3.1.

For achieving the mentioned objective, the main research question of this research is:

What factors influence the organizational readiness for the deployment of Artificial Intelligence in semiconductor companies?

The proposed framework is developed through 14 case study interviews in a semiconductor equipment company. The existing AI readiness factors in the literature and potential readiness factors identified from the industry expert interviews are taken into consideration in the development of the framework. The final AI organizational readiness framework consists of 20 influencing factors in six dimensions.

To answer the main research question, four sub-questions are formulated.

1. What are existing research frameworks on AI organizational readiness?

The first question serves as the starting point on organizational AI readiness research in semiconductor manufacturing by review the existing theoretical framework. This question is answered by conducting a literature review on the existing AI organizational readiness framework. The overview of frameworks can be found in section 2.1.2. As of now, there is not much research on organizations' readiness for AI. Alsheibani et al. (2018) first explore AI readiness using the TOE framework. Pumplun et al. (2019) extend the TOE framework with AI-specific factors to investigate AI readiness and identify subcategories for existing ones. Alami et al. (2020) explore the organizational readiness for integration of artificial intelligence in health care delivery and propose four improvement dimensions: needs and added-value assessment; workplace readiness; stakeholder acceptance and engagement; technology-organization alignment assessment; business plan: financing and investments. Jöhnk et al. (2021) conceptualize AI readiness with 18 factors and categorize them into five aspects: strategic alignment; resources; knowledge; culture and data.

2. What are the influencing factors of AI readiness on the organizational level in existing literature?

The objective of this question is to find out influencing factors for AI organizational readiness from existing literature. This question is answered by extracting typical readiness factors from existing frameworks in section 2.1.3. Typical factors are extracted from existing AI readiness frameworks such as Needs and added-value assessment, Top management support, Stakeholder engagement, Financial budget, Talent, IT infrastructure, Multidisciplinary team, Data availability, Data quality, Competitive pressure, Customer readiness. More detailed information in terms of influencing factors can be found in Appendix A.

3. What are AI use cases in semiconductor manufacturing to direct the industry-specific organizational readiness research?

This sub-question aims to find out AI use cases in the semiconductors to show a clear picture of AI applications in the semiconductor industry and indicate opportunities. Applications of AI vary across industries, it is essential to know how AI can be used in semiconductors because research on organizational readiness should be embedded with clear purposes. This question is partially answered through a literature review in section 2.2. Then eight external expert interviews are conducted to give a more holistic view of AI use cases across the value chain which is shown in section 4.1.2.

In the research and design phase, it is meaningful to incorporate machine-learning technologies into the **IC design & verification** process to provide solutions to complex design problems, identify potentially buggy design elements, and facilitate a more efficient design flow. In semiconductor manufacturing and testing, **predictive maintenance, pattern modeling, defect inspection, virtual metrology, statistical process control** can be developed to optimize the manufacturing and testing process. **Yield management** and **integrated fab automation** level can be improved through an optimized manufacturing process which is critical in semiconductors. Moreover, there is a trend of a **design collaboration** between EDA companies, equipment vendors, and foundries to make manufacturing-ready designs and shorten the build-and-test cycles. In addition, **unit traceability** throughout the chip life cycle can help diagnose where the problem is so that it can be fixed accordingly. AI will enhance other business functions in operations, for example, **capacity planning**, **demand forecasting**, and **inventory optimization**. But they are not specific to the semiconductor industry and are widely used in other industries.

At the same time, the challenges of AI deployment in the semiconductor industry are summarized in 4.1.3. Semiconductors are very concerned about compromising the confidentiality of the information and tend to be quite cautious when it comes to data sharing. Semiconductor manufacturing requires a high level of accuracy and there are hundreds of parameters within each step that add operation complexity. Commercial off-the-shelf solutions are not effective and need to adapt to the semiconductor manufacturing context. What's more, there is an intrinsic challenge in AI as it gives the system a probabilistic rather than a deterministic answer. Trustworthy data and good modeling techniques are important to increase the accuracy of predictions.

4. What are empirical AI organizational readiness factors in a semiconductor equipment company?

With a deeper understanding of the semiconductor industry and AI use cases in this sector, AI organizational readiness framework can be better formulated. This sub-question aims to find out empirical influencing factors of AI organizational readiness by conducting a case study at ASML, a semiconductor equipment company. Through 14 case study interviews, 20 empirical AI organizational readiness factors are identified finally.

In the strategic alignment dimension, there are four influencing factors which are **1) needs and added-value assessment, 2) bottom-up proposal/innovation lab, 3) top management support, 4) business model innovation**. In the resource dimension, there are **5) talent, 6) financial budget, 7) IT infrastructure, 8) competence center**. In the process dimension, there are four readiness factors**: 9) multidisciplinary team/collaboration, 10) agile way of working,**

11) employee training, 12) business process standardization. Regarding data dimension, **14) data availability, 14) data governance, 15) data platform** are included. In the AI model cluster, 3 new readiness factors are identified, **16) explainable AI with domain experts, 17) context-aware modeling, 18) model operation**. In the external business environment, there are two AI organizational readiness factors which are **19) peers, competitors and software vendors and 20) customer demand**. They also have a positive influence on AI deployment.

The distribution of 20 readiness factors and characteristics of each influencing factor are provided in section 4.2.1. As a result, the AI organizational readiness framework is developed which can be seen in Figure 13 in section 4.3.1 and the main research question is answered.

5.2 Contributions of the research

5.2.1 Theoretical contribution

First, this study addresses the gap between academia and practice as most attention to artificial intelligence was paid to modeling steps with numerous new model architectures in academia at the moment while the scientific research on applying AI models to real-life problems and realizing business value has received insufficient attention (Jin et al., 2019). This study focuses on the organizational readiness aspect of AI, aiming to enable organizations to move forward in the field of AI beyond technical AI and reap the business value of AI.

Second, this study contributes to the conceptualization of AI readiness factors on an organizational level (Alsheibani et al. 2018; Pumplun et al. 2019; Jöhnk et al. 2021) by focusing on the semiconductor industry. This study summarizes typical readiness factors such as talents, budget, IT infrastructure, employee training, top management support in existing literature in 2.1.3. Through industry expert interviews and case study interviews, 20 readiness factors in 6 categories are identified as AI organizational readiness factors. Furthermore, 20 propositions on AI readiness in semiconductor organizations are made indicating their positive or negative influence on AI organizational readiness. Existing readiness factors are examined and new insights on them are provided as well. For example, regarding IT infrastructure, this study finds a hybrid cloud infrastructure positively influences AI organizational readiness. Among 20 readiness factors, 10 readiness factors are newly identified in this research such as innovation lab, agile way of working, competence center, data governance, context-aware modeling.

Third, this study provides new insights into the multi-dimensional framework of AI organizational readiness. TOE (Technology–Organization–Environment) framework is used in Alsheibani et al. (2018) and Pumplun et al. (2019). Jöhnk et al. (2021) distinguish five dimensions: “strategic alignment, resources, knowledge, culture, data”. In this study, I propose a six-dimension framework that includes “strategic alignment, resources, processes, data, AI model, external business environment”. This study distinguishes AI-specific readiness factors which are included in “Data” and “AI model” aspects while the other four aspects are general readiness factors. Through these six lenses, an organization can have a holistic view of its capability to successfully deploy AI.

5.2.2 Practical contribution

Nowadays, digital transformation is one of the most important initiatives to be undertaken in many organizations. One of the main enablers of digital transformation is AI. However, organizations often struggle to realize AI's business value. This study aims to help companies in the semiconductor sector cross the chasm between industrial practice and AI technology.

AI use cases across the semiconductor value chain are mapped to give a holistic view of AI applications in semiconductors in this study. It also provides an outlook on the opportunities and challenges associated with AI deployment in semiconductor companies.

The six-dimension AI organizational framework with twenty readiness factors derived from this study can serve as an assessment tool for companies that target AI. What’s more, it can be viewed as comprehensive guidance for decision-makers, managers, and project teams for faster and better development and deployment of AI.

5.3Limitations of the research

First, a limitation of the research is that it mainly concerns large companies as there is a wave of consolidation in the semiconductor industry. Small and medium-sized companies may not be affected by all the factors identified in the framework.

Second, this research does not have a large sample (14 case study interviews) and is a qualitative study instead of a quantitative study. In this respect, it may raise the issue of external validity. Nonetheless, when a researcher is trying to gain novel insight into a new subject, focusing on a small number of cases may often be justified (Saunders et al., 2009).

Furthermore, the scope of this study is AI organizational readiness. But there may exist synergies with other digital technologies and it is out of scope for this research. It makes sense to compare organizational readiness with other technologies. And the intercorrelated relationship of readiness factors is discussed little in this study.

5.4Recommendations for future research

This research opens up a range of interesting areas for future research.

First, the developed AI organizational readiness framework can be verified with startups, small and medium-sized companies in the semiconductor industry to evaluate the proposed readiness factors empirically. Other case studies can be used to fine-tune the proposed conceptual framework and enhance its generalizability.

Second, the proposed influencing factors in AI organizational readiness framework can be further improved by quantitative measurement with weightings. Quantitative performance measurement methods should be implemented for each of the readiness elements. Then a weighted average assessment in conjunction with the importance-performance analysis can be performed to help organizations assess and illustrate their readiness. This will enable businesses to determine how ready they are and allow them to prioritize their efforts to improve. It will assist them in digital transformation and moving towards the fourth industrial revolution.

Finally, it will be interesting to look at how factors interact and what mechanisms are at play based on the research results. It is also worth exploring how a combination of different readiness factors influence AI organizational readiness. What’s more, future research can be done to track how a certain factor changes over time in the process of building AI capability in an organization to give more insights on achieving a successful project with fewer obstacles.

5.5Reflection

5.5.1 MoT relevance

This research is conducted in partial fulfillment of the master's degree in Management of Technology (MoT) at the Delft University of Technology. The curriculum of MoT aims to deliver knowledge of how to analyze technologies, their effects on the business, and how to implement these within a firm's organizational context. The purpose of this research is in accordance with the program by investigating the organizational readiness of artificial intelligence with empirical evidence in the semiconductor industry. This study can help companies in this sector with the deployment of AI technology which is an effective enabler to drive business value and offer unprecedented profitability opportunities.

The multidisciplinary nature of this thesis, which combines technology with organizational analysis, illustrates the type of study that MoT alumni should demonstrate. Furthermore, the study covers various courses within the MoT curriculum. What I learned from MOT1412 Technology Dynamic that adoption and diffusion of technology are not only functions of technology but are also driven by social factors provides direction for this research and guides me to conceptualize the framework by taking both technological and social factors into account. The course MOT2312 Research Methods helps me with the design of the research and how to do qualitative data analysis. The course SEN1611 I and C Architecture Design provides me with ICT-architecting, design, and governance knowledge and data management knowledge which helps me better understand and develop AI organizational readiness factors such as IT infrastructure, data platform, and data governance. The lesson learned from the course MOT1435 Technology, strategy and Entrepreneurship helps me have a better understanding of the semiconductor value chain and map out AI use cases. The course MOT1531 Digital business process management gives me insights on strategic alignment and business process improvement dimension in the proposed framework. The course MOT1524 Leadership and technology management helps me observe the importance of knowledge management in an organization. Several factors in this study such as competence center, innovation lab, external push reflect the lessons learned.

In summary, this study provides an organizational readiness perspective on how organizations can use AI technology to develop products and services that provide added value to customers on the one hand and improve corporate productivity, profitability, and competitiveness on the other hand. The content of this research reflects the knowledge and skills belonging to the curriculum of the MoT program.

5.5.2 Personal reflection

To reflect more on the personal experience and research process, I learned how to set up and carry out a qualitative study, how to plan and manage the project.

Importantly, scientific research should always begin with a research gap. At the beginning of my graduation project, I focused less on the scientific literature and put more effort into finding the practical problems for AI deployment from industry reports. The research question is hard to formulate without the research gap from the scientific literature. After several discussions and iterations, I finalized my thesis topic on AI organizational readiness.

I learned a lot on AI topics which I am always excited about. AI opens up a great opportunity for organizations but it is also challenging in terms of successful deployment. So it is critical to take actions that can enable AI-powered transformation to avoid wasteful investments and costly failures. Moreover, I gained an in-depth understanding of semiconductor manufacturing and AI use cases across the semiconductor value chain through which are necessary for developing industry-specific readiness factors.

In addition, I got the opportunity to talk to many brilliant minds in the case study interviews through which the AI organizational readiness framework is developed. The experience enables me to have a helicopter view of how ASML is taking advantage of artificial intelligence and gain a deeper understanding of its holistic lithography approach. More specifically, I learned how different departments collaborate and make coordinated efforts, how a project is proceeded in different phases, what kind of infrastructure and platform they use, etc. I highly value such kind of know-how knowledge.

Last but not least, it's a new experience for me to analyze qualitative data and I find it useful as a way to interpret and structure the meanings that can be derived from data with inductive reasoning processes.

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Appendix

Appendix A: Organizational artificial intelligence readiness frameworks

Count	Theory	Category	Factors	Definitions	Method
1	**AI-readiness at firm level adapted from TOE framework** Alsheibani, S., Cheung, Y., & Messom, C. (2018)	Technological readiness	Relative advantage	the perceived benefit (the degree to which AI is better than other competing technologies) of adopting AI at the firm level	a quantitative approach using an online survey instrument (5-point Likert scale) C-level and intermediate executive in charge of the information system of SMEs in both private and public service organizations in Australia
			Compatibility	the extent of the innovation and its ability to provide value and experience while addressing the needs of the expected adopters	
		Organizational readiness	Top management support	the engagement of a top-level leader for IS/IT implementations Top management commitment can also have a significant positive influence on new technology adoption in terms of articulating a vision, providing capital funds, and allocating resources	
			Resources	human, enterprise, and information technology resources are critical to adopting innovation at the firm level. Technology resources refer to computer hardware, data, and networking that are essential to adopt new innovation	
			Organization size	the size of the organization directly affects the adoption of innovation, larger organizations have more financial and technical resources	
		Environmental readiness	Competitive pressure	the threat of losing competitive advantage, which motivates an organization to adopt an innovation	
			Government regulatory issues	the assistance provided by the government authority to encourage the adoption of AI innovations at the organizational level	
2	**Extended and deepened framework**	Technological factors	Relative advantage	the perceived benefit (the degree to which AI is better than other competing technologies) of adopting AI at the firm level	in-depth expert interviews

	for AI adoption adapted from TOE framework Pumplun, L., Tauchert, C., & Heidt, M. (2019)		Compatibility - business processes - business case	compatibility can be divided into two subcategories: business processes and business cases; business processes in the company must be adapted to the new requirements that arise from the use of AI, it becomes necessary to introduce agile forms of work; AI must be seen as a tool for a purpose and cannot be viewed in isolation	
		Organizational factors	Culture - top management support - change management - innovative culture	the engagement of a top-level leader for IS/IT implementations Top management commitment can also have a significant positive influence on new technology adoption in terms of articulating a vision, providing capital funds, and allocating resources	
			Resources - budget - employees - data availability/protection/quality	1 a dedicated AI budget, which does not entail any obligations to meet performance targets, will have a positive impact on the adoption of AI in companies 2 the availability of data scientists and developers with appropriate expertise, domain knowledge as well as the willingness of users to train AI systems over time will have a positive impact on the adoption of AI in companies 3 the availability of extensive, meaningful, and high-quality data will have a positive effect on adoption of AI in companies	
			Organizational structure	Departments that keep relevant data to themselves, an overreliance on status quo as well as slow and bureaucratically shaped corporate structures will have a negative effect on the adoption of AI in companies	
			Organization size	the size of the organization directly affects the adoption of innovation, larger organizations have more financial and technical resources	

		Environmental factors	Competitive pressure	the threat of losing competitive advantage, which motivates an organization to adopt an innovation	
			Industry requirements	Industry-specific properties (e.g., specific regulations, customer group) will, depending on their nature, have both positive and negative effects on the adoption of AI in companies	
			Customer readiness	Demanding customers will nudge the companies to design individualized, intelligent products and thus will have a positive effect on the adoption of AI in companies	
			Government regulation -GDPR -Employees' council	Strict laws regarding the processing of personal data will hamper the training of intelligent machines and the review by a strong employee representative body will slow down and inhibit the introduction of new technologies. Thereby both will have a negative effect on the adoption of AI in companies	
3	**Organizational AI Readiness Factors** Jöhnk, J., Weißert, M., & Wyrtki, K. (2021).	strategic alignment	AI-business potentials	AI functions are highly versatile and broadly applicable AI-business potentials ensure that AI adoption is beneficial and suitable for the organization	a qualitative research approach in-depth interview study
			Customer AI readiness	AI use requires an understanding of the complexity and lack of transparency of learning algorithms. Customer AI readiness enables internal or external customers to appropriately use AI-integrated offerings	
			Top management support	AI's inherent complexity poses change not only within but across organizational levels which requires top management commitment. Top management support signals AI's strategic relevance to the organization and fosters AI initiatives	
			AI-process fit	AI-based systems are more precise if processes are structured and provide standardized data input AI-process fit through standardization, reengineering, and implementation of new processes facilitates AI adoption	

			Data-driven decision-making	AI-based systems are fundamentally data-driven and require openness to incorporate such insights Data-driven decision-making fosters AI adoption because both utilize data and statistical methods to gain insights	
		Resources	Financial budget	AI-based systems require high investments to tailor assets and capabilities to the unique context and data. Strategic allocation of the financial budget for AI adoption supports the overcoming of initial obstacles and uncertainty	
			Personnel	AI adoption requires a broader spectrum of different roles and know-how for core business use AI specialists and business analysts with AI know-how facilitate AI adoption	
			IT infrastructure	Deploying AI poses high workloads and data storage requirements IT infrastructure enables AI-related activities and AI integration	
		Knowledge	AI awareness	AI's underlying concepts, e.g., machine learning or the autonomy of data-based decision support, are hard to grasp. AI awareness ensures that employees have adequate understanding and expectations toward AI	
			Upskilling	AI-based systems in core business require every employee to have a basic understanding of AI. Upskilling enables employees to learn and develop AI or AI-related skills	
			AI ethics	AI-based systems are at risk for biased learning and unethical outcomes AI ethics comprise measures to prevent bias, safety violations, or discrimination in AI outcomes	
		Culture	Innovativeness	Employees' fear of AI-induced job loss threatens proactive innovativeness Innovativeness increases employees' willingness to change the status quo through the application of AI	

			Collaborative work	AI deployment relies on integrating different perspectives, i.e. domain, data, and IT Collaborative work enables employees to work in teams and combine different skills	
			Change management	Employees’ lack of understanding and fear of AI threaten the acceptance of AI-based systems Change management helps employees to understand and cope with AI-induced organizational change	
		Data	Data availability	AI-based systems learn through different data types and large data amounts Data availability within the organization fuels AI solutions	
			Data quality	AI-based systems achieve better results the higher the quality of the data they learn with Data quality ensures accurate AI outcomes	
			Data accessibility	AI personnel require access to relevant data sources for deployment Data accessibility facilitates AI experts to easily prototype and develop AI solutions	
			Data flow	Initial and continuous training of AI-based systems requires smooth and automated data flow Data flow between its source and its use ensures high data accessibility to AI experts	

Appendix B: Industry expert interview protocol

The main question being considered is how can semiconductor ecosystem players capitalize on AI opportunities and gain a deeper understanding of AI use cases in semiconductors.

Brief introduction of the advisor's career/experience

1. What AI use cases in the semiconductor industry have you been familiar with or working? What are your thoughts on those AI use cases?
   e.g. Predictive maintenance, statistical process control, virtual metrology, fault detection and classification, capacity planning, demand forecasting
2. What do you think are the challenges in the utilization of data?
   What are the unmet demands in fabs?
   How data is shared among players in semiconductors (EDA, Fabless, Foundry, IDM, Equipment provider, OSAT)? How data can be better utilized for analytics?
3. What are some new value propositions in the semiconductor industry regarding AI-enabled applications you can think of?
   What's your view on equipment providers' attempts to offer added value for manufacturers?
   What actions can firms take to monetize AI opportunities?
   How is your organization or other semiconductor companies you know developing AI?
   When did it start and how many people do you have working on AI-related projects?
4. What kind of strategy do you have and what AI use cases do you focus on?
   Do you develop AI solutions with an in-house team or off-the-shelf?
   What kind of strategy do players in other segments of semiconductors have?
5. What are some best practices to deploy AI for semiconductor companies?
   Is it a top-down or bottom-up process? Which one is better in your view?
   What kind of organizational activities should be done to facilitate AI deployment?
   What are some challenges you can think of and how those challenges should be solved?

Appendix C: Case study interview protocol

1 Introduction

1) Participants
- Interviewer
- Interviewee: Name, function within the company, task regarding AI project
2) Procedure
- Discuss confidentiality and recording
- Explanation interview agenda and goal
3) MSc. Thesis

Research statement

- What factors influence the organizational readiness for the deployment of Artificial Intelligence in semiconductor companies?

Definitions

- AI organizational readiness: AI organizational readiness is the extent to which an organization has the ability to reap the benefits of AI.

Experience

- Could you give a short summary of the AI/ML projects you are involved in?

2. AI organizational readiness

- How did you prepare for the AI project?
- What resources were required for the AI project?
- What activities were required for the AI project?
- What went well in the AI project?
- What went bad in the AI project?

3. End questions

- Thank the interviewee
- Discuss the process, verification of interview, and sharing of the results
- Closure

Appendix D: Interview invitation Email

Hi <interviewee name>,

I am Chenlu and I am an intern at the Strategic business development of the Strategy & President Office in ASML. I study in a master's program Management of Technology at Delft University of Technology, Netherlands. Currently, I am working on a project to explore business opportunities of AI in semiconductors and at the same time I am doing my master thesis with the topic “AI organizational readiness”. I got to know <interviewee background>. I believe your input will be of great help.

I have done some desk research on AI use cases in semiconductor manufacturing, e.g. computational lithography, predictive maintenance, statistical process control, virtual metrology, fault detection and classification, demand forecasting, yield prediction. I have also carried out some interviews with experts from <8 semiconductor company names> to gain in-depth knowledge of AI value creation, AI use cases across the value chain, best practices for AI deployment.

Now the focus of my work is to identify and validate important factors of “AI organizational readiness” (the extent to which an organization has the ability to reap the benefits of AI) within ASML. I would like to have an interview with you to know your perspectives and experience on that, e.g. strategic alignment (Needs and added-value assessment, Top management support, Stakeholder engagement); resources (Financial budget, Talent, IT infrastructure); process (Multidisciplinary team, Agile way of working, Employee training); data (Data availability, Data quality); AI model (Non-biased and explainable AI model); business environment (competitive pressure, customer readiness)…

I sincerely hope I can have a 30-minute interview with you or your team member. Thanks for taking the time to read this email and looking forward to your reply.

Best regards,

Chenlu

Appendix E: Transcript categorization example

2: Yeah, so if you look, in our case, we are working on IBM Watson products. I'm not sure if you heard about it. That's our cognitive search engine. And that was actually initiated like two years ago by our CEO Peyton Manning himself. So there was already top management attention on this topic from the start. And then yes, what you said we first did some proof of concepts to identify. Okay, what will be the most suitable use case, which we want to investigate for? So after doing couple months, or some proof of concepts, and eventually, we came to a use case, and then again, approval was given also from senior management to proceed in a more, let's say, proof of value, set up like a pilot. Okay, we think this can bring us value. Let's make it more formal. let's stretch your eyes it, let's further develop it, enhance it. And then again, let's see how that will turn out. So after proof of concept, we did a pilot. And then after that, why did we see in my case, not because it was already very much driven top down. So from our very senior management level, there was a lot of buy in, a lot of attention and a lot of support. So those struggles, I did not encounter to get the budget, or to get the right attention, those kinds of things. In my case, were not really valid. The only thing what was a little bit difficult at a certain point in time is to, to explain this and how this works. Because there's a lot of clarity, let's say within the company, on the technology itself. And that makes people a little bit hesitating or having now is it really that helpful. And once they see it, so you really, you really need to have already some kind of proof, which is relevant for the company to get, let's say, by also on other layers. If you only do a talk and say how great it is, and how great it can be and those kinds of stuff without really having something concrete to show or to demonstrate, then I think you will have much more difficulties to you know, to get to a point where you really can kick off and start industrializing a solution within the company. Yes. And as we obviously have a system which was working which was actually quite good working, that whole process made it very much easy to get through all those loops, you know, approvals buy in, etc, to really do the project. So I think it's very much depending on the importance indeed what you said the buy in to proceed and luckily, I had all those things in favor of the project, because it was already top down driven. So I

Chenlu Song
Top management support

Chenlu Song
Top management support
Top-down driven

Chenlu Song
Prove the concrete value

Appendix F: Industry expert interview quotes

Challenge 1: Conservative attitude towards data sharing

E2: They work to prevent that, and they might be a little bit more conservative than other companies in that respect, number one because of what I just described, and number two because there's secrecy on the process of how the company makes their products and a huge reluctancy to share any of that process with the outside world.

E4: Adoption of cloud is another place where, I would say, the semiconductor ecosystem has been much slower to adopt as compared to other industries. There are hardly any tools on the cloud, hardly any EDA tools on the cloud. The fab-less customers are very, reluctant to put any of their designs on the cloud. The foundries, as you pointed out, are paranoid. They don't want any of their process data leaked out, so they're not putting anything on the cloud.

E4: the reality is that the semicon ecosystem has been way, way, way too slow in adopting the cloud as compared to other industries.

E5: Actually, today, the limitation for really doing that isn't a technology limitation. It's a business limitation. It's getting all that ecosystem to be comfortable and how to share the end-to-end data. I couldn't tell you exactly how they're using AI in the factories, because they try to keep their IP completely secret.

E6: That's typically locked by the fab host from all these different tools, and that can just be looked at independently.

E6: They're very leery to share their knowledge. They all have their own automatic process control activities and machine learning and AI groups looking at that stuff. They view that as a competitive advantage.

E6: Again, there's resistance for data security reasons to putting servers in, but they realize that, in some cases, they need to. So, progress has been made on that front.

E7: the challenge is you got to work at a very high level with that customer, to convince them that this is a great thing to do. That there'll be total integrity in terms of how we use that data, and that it will be protected

E7: But to think that you're actually tying into their portal to get their datasets across the fab, etc., they're going to be very cautious about that.

E7: There will be an agreement that's very, very closely defined with very tight boundary conditions at the starting of things

E8: So, the fabs have a complicated relationship with their equipment makers on this front because what the fabs would like to be able to do is get all of the interstitial data inside every piece of capital equipment and really monitor it and control the process.

Challenge 2: Off-the-shelf solution does not work

E1: they have been applying a lot of visual recognition AI algorithms to a lot of their modeling. Along with that, because the data in semiconductor manufacturing is a bit different, what I know is that after applying this deep learning algorithm, they're still looking into coming on with their own unique algorithms that are more catered towards semiconductor manufacturing.

E1: I think most of the companies are trying to do that as well, is that they want to have a bit of an in-house analysis as well. I think that's why they started to aggregate all this different data from different equipment's from different vendors.

E1: It's way much more complicated and every step has possible tens and hundreds of different variations and combinations. Even though we have a lot of data, the data contain a lot of variabilities. Implementing the off-the-shelf algorithms definitely doesn't work.

E2: So when we have the 7 nanometers go to 5 nanometers, and in comparison to previous nodes, they are increasing about three times the data size

E2: As they customize that database, they use it for their own input data and those types of things, and it gives them visual, almost like a Tableau, but not Tableau. That was done in-house.

E3: They have a lot of data generated every day, so every day they maybe have generated a trillion of the byte of data will be accumulated. You can understand the semiconductor industry is a process industry, Every process is critical and matters.

E4: all the development is in-house because it does require a fair amount of knowledge about their own tools, which is going to be very difficult to acquire from outside.

E5: Most of the ones that are the leading ones right now are doing it with in-house development, but then they're combining their early findings with partners so that they can take the actual actions, the insights, and be able to deliver them in production.

E6: and any type of preventive maintenance is going to be very different for different tools. In that sense, you have to develop a unique framework

E6: the fabs try to have more deep expertise where they're actually able to maybe develop these machine learning and train the models themselves.

E6: But, without a doubt, the instrument companies would have in-house AI and ML capability.

E7: That's another big challenge in terms of getting that visibility and usability across the fab itself, not just within the tool itself.

E7: They have a tremendous imperative now to really develop their software capability, their AI capabilities, in-house.

Challenge 3: AI intrinsic challenge – probabilistic rather than deterministic

E1: It works in the previous data, but there's no guarantee that it'll work in the future data that's actually happening in real-time. In that aspect, you need a meticulous design on how to implement the algorithms in an actual manufacturing process.

E4: The application to which you apply AI needs to have the tolerance to absorb a probabilistic decision. If your application requires a certain decision or, as it is called in the computer science literature, a deterministic answer, then you will not be able to apply AI to it, because AI techniques of all forms only give you a probabilistic answer. Therefore, your application or your problem must have the tolerance to absorb a probabilistic answer.

E6: The biggest challenge is taking the process engineer out of the loop. Right now, process engineers analyze data with very sophisticated tools and make the decisions around if and when and how to adjust the process tools. And automated process control, where that loop is completely closed by software, on one hand, I think that people believe that there's value in that and that there's a direction to go. And at the same time, people are kind of conservative that there's a barrier to actually doing that, given the risk of the yield excursion.

E7: So, there is a level of confidence.

E8: As of yet, the AIs are not smart enough to do it on their own, and humans have to supervise parts or all of the process to get it to converge, and a lot of the different models don’t converge, and you have to know when to throw them out and try a different one.

Appendix G: Case study interview quotes

Needs and added value assessment

C1: You need to have already some kind of proof, which is relevant for the company to get, let's say, by also on other layers. If you only do a talk and say how great it is, and how great it can be and those kinds of stuff without having something concrete to show or to demonstrate, then I think you will have much more difficulties to you know, to get to a point where you really can kick-off and start industrializing a solution within the company.

C2: So it's the use case that has to be connected to the value. And the question is there other than how well the business case for that AI proposition is? So that's something that the proposition itself has to take care of, like, if you have an idea that, hey, I want to do this, but then what is the impact of it? And maybe it can be that like, you don't need such a strong machine learning different approach. You could have just had a sensor in that place to detect something else. And that's a deeper and more accurate approach.

C3: I mean, the customer has an issue, and you quantify the value of the issue for the customer. And then you come up with a solution that solves that issue. And then this is where you do your normal pricing on the product. So this is how you investigate the opportunities. And once you have identified that customer opportunity, you look at how can I capture it? What can I solution Do I need to build? And then AI is one of the elements that can be that can address the issue.

C3: AI, for instance, is very good with image processing type of use cases. And as a way of achieving if I can have a system that is at least as good as a human being sometimes even better idea and then the engineer do something more valuable

C4: We do value it. We all know predictive maintenance is useful for us for many different reasons. It is the value the complete value of predictive maintenance that is difficult to realize at ASML. But at the use case level, it is easy to realize, you understand what is the problem and then you if you say if you have a predictive model, which can indeed predict one month in advance, you can then understand how much the customer gain and how much will ASML gain.

C5: So we will create a one-pager, one-pager is a description of the project, the added value, and claim resources. so resource claim is really important. We do assess it in two ways. One is the quantitative benefit. So you can say, the money you save, or the FTE you save. It can also be qualitative benefits. So for those things that are difficult to translate into Euros.

C6: So this is a trend to do a bottom-up market estimate for the data-driven applications from the data-driven applications. We need number one, to be able to show that it's an interesting area to invest in. And there is either a competitive threat or there is big market capture. And number two, we need to, once we have identified that we need to give ourselves the means and strategically decide to focus on finding data products that can bring value to our customers,

C6: it's time to market because of the runtime of these optimizations and much, much faster than what was before expected by PC software.

C7: the added value for the ASML is obvious because we can, yeah we can, we can help using empower machine learning to help customer detect their failed wafers. And for the customer it's Yeah, the customer is also very beneficial because, yet every customer has its limited capacity to do investment or to detect which wafer will be failed.

C8: because there's an alongside the revenue for the customer. And then on the ASML side, it's helpful to reduce cost, so we can optimize planning…

C9: So some of our products are leveraging neural networks, machine learning in general, to improve accuracy and others to improve runtime. So we have been a few of the maximum to do both at the same time.

C10: For us, it's important to develop the best tool. And if AI is helping there. I'm fine using it if artificial intelligence is too cumbersome and we need to go to physical models

C10: In metrology is used for two things. The first thing is to do something faster. It can be that the physical model is computationally much more expensive, which means that it takes longer to do the computation.

C11: we can at least identify and investigate if there are potential benefits for ASML. So then if we see that, then we have to propose a proof of value.

C12: So the result after let's say three months of experimentation is that we can do a really good business case analysis and decide from that moment on, do we want to proceed with this kind of technology or do we just stop.

C13: they have a nice business perspective, but then we can feed into that saying this will help your business be effective because these new algorithms and these new libraries that can be utilized and implemented and then we show that they can be in research and then we hand it over, and then it gets scaled.

C14: if you really like to go upstream as far as possible and try to predict what happens downstream to prevent issues. Then there's only one way and that's looking at the entire value stream. So that's what we try to do as much as possible.

Bottom-up proposal/Innovation lab

C2: up because of the top-down people, it's not possible to have such an in-depth view at all.

C5: we have topic teams, they really have knowledge of data and process, and they say, Okay, I want to try this product. Then they first well discuss in the same pop. It's a project board. And so the management will discuss and approve that if it's proved the related resource can be claimed.

C9: in some cases, we realize that certain things that we've been doing for one part actually can potentially carry over quite well to have value there

C12: And we have initiated some innovation labs as well, where we experiment with new technologies and how that can be of value for ASML, but specifically in the, let's say PLM domain

C12: in the innovation area we see let's say some initiatives popping up. There are different sources for that. Sometimes it's just let's say some good ideas from our engineers, sometimes it's just good ideas from the people in my department.

C12: last year we even had a Dragon's Den kind of approach, where people had to pitch their idea to also, at least give a bit of a hunch, on, on the business case, but it's not solid, let's say, approved kind of business case yet, because that's not the phase, where we're in innovation, exploring what's the value potential value for ASML.

C13: because I'm in research, so I kind of do what I do is technical marketing so we read journals and think, Oh, this is interesting. I bet we can make money with it here and then we prototype something, sometimes before even someone wants to pull it we say this has value. And then we go pitch it and sometimes it lands in an application like it Brian.

Top management support

C1: So from our very senior management level, there were a lot of buy-ins, a lot of attention, and a lot of support.

C2: It's really on the radar of the senior management, that like this is the improvement point

C14: We all have the gut feeling that this should be leading to somewhere also our director and also the vice president who initiated this initiative. Everyone believes in so much stat, even if we cannot initially prove the value yet. Now that we have to see to what extent it was already set to some extent we still are already able to do best everyone believes that should bring, even if we cannot prove it should bring something, and we were in the middle of this how-to, to show that is to make this tangible

C14: Our director also said, maybe it's even interesting, to make it a separate workstream within our team to get focused on this. So it's something. We believe in and hopefully can show benefits because we think it might be the future.

Business model innovation

C2: I think more business model needs to be explored. If I had the answer to that, I would also I would just propose it to the management that, hey, we should be doing this. But we need to explore business models that are currently not enabled are currently not in practice. And if you look at the currently existing business model, and how long they existed, for, they're pretty, there's nothing new about them, which is fine. But it's not that it's not working. It's working completely fine. But there needs to be maybe some emphasis towards export, or business models that are new, or future. Yeah, that could be an activity of its own that, hey, let's have like maybe five working sessions, stakeholders and that people are finding out what is the right business model?

C3: This is interesting because I think the industry is near the tipping point. Where indeed, they need to innovate in their business model. Because what you see happening is that the data alone doesn't bring the value because you need domain knowledge to know how to use it, ML will only take you so far, you need to bring in your domain knowledge to make some sense of the data before giving it to the machine learning model.

C3: So it means that the new business models require customers and ASML to share the value because customers bring the uniqueness, which is the high data volume, ASML brings the uniqueness, which is high domain knowledge. And I think unless we have defined the bridge from a model accuracy to a factory gate, it will be very difficult to quantify the benefits and sell the solutions.

C4: We are traditionally a hardware company with the hardware. Yeah. But we had been ignoring the service sector completely. So if we should indeed make this data science on the products which we are building around data science, we need to sell these additional services to the customer. We are in a position to do it. And we have the data, we have the knowledge to build these models. If we have this, will not only benefit some money, but I think we will also tap the huge business potential. service sector. The lottery is very big in medical care. This is very big in the airline industry. I think it can also become very big in ASML as well.

C6: There definitely are some areas from the playground where we're at today. So setting in a perpetual way is not always the most efficient, otherwise, we'll be either the customer will be paying way too much initially for a reduced value, or we will be setting the tone for the product for this value, but then we will keep working on it right so at some point, we, we lose more and more value than most, the longest time we work on it so it's not a win-win model really, which is why we're looking at a time-based license type of model, which can be done in two ways. So this service part. So that's what ASML. Same thing for companies like AMAT and KLA, their service revenue, and is a big thing they want to develop into growing, and big. And they Yeah relatively big part of their service is improved by having a bit of software tool. So that's across the industry.

C8: In the future, we want to charge money on it, by deferring, as well as service contracts with customers if you buy a scanner and you have a book service contract that customers have to pay a yearly fee for us to serve it.

C9: we do sell our products as separate licenses

C9: The question is can we take, for instance, the same measurements and feed that directly into a model that simply tells us what the best mask is associated with that. And that is certainly something that we're actively working on

C10: But which serves as where they can only access the kind of web interface, and they have the kind of app store on what functionality they'd like to have. Yes, technically it is possible, but politically or customers need also to allow for this

C12: but I know that ASML wants to professionalize the data provided to our customers in a better way. So, to make it more of a standardized kind of product so you buy our machine, but you can also buy a license then to interact maybe on API's or I don't know what to actually extract the data in a more, let's say formal way. But I know that they are working on that but that's the virtual control platform.

C13: To be honest with you I see at some point, this is going to sustain, and then we were going to provide a service and then what, what is the foundation of that service. Is it our expertise? I don't think it's going to be AI models because like I say we're already way behind Google and Facebook, we might be able to outsource that with our domain knowledge with our data and build something like maybe with an IBM Watson, something like that.

C13: it's hard to compete in terms of selling software. We can capture the value, but the fab is going to squeeze that margin in any way they can, by saying okay, just give us the data and we'll do our own, but like I said there's. If you have software that is valuable that is informative. That discussion is easier, because the fab will just buy it, rather than doing it themselves, too high risk.

Talent

C1: We have data scientists within IT, but obviously, they are scarce. So it's, I mean, it's always difficult to get one.

C9: it's really hard to find people with the data science background that we need because there's plenty of machine learning but not specifically for the kind of things that we do. It's sort of a niche.

C9: And so if we get a candidate, either we have to find a candidate who already has experienced an OPC and might be a good candidate for coming up to speed in machine learning, or we have to find look for candidates who have a background in machine learning, not exactly our background in machine learning, which is unfortunate but that's the way it is. And because ours is a slightly different problem, all EDA has this problem.

C14: Yeah I think that's exactly what I just try to say that also our director is also having his ideal so we internally had a discussion. I think what we really don't want also knowing ASML knows a little bit, that on this kind of content, we don't want to work together with a black box supplier.

Financial budget

C1: As said, because of the senior management and data and the importance, we always got sufficient budget to proceed

C4: In the beginning, it was a challenge to prove. But once we have proven, we have the budget.

C5: you need some budget or if you say, I want to do it quick. Within a month or two, and then you go to Deloitte or Accenture or whatever, the third party.

C8: slowly but surely. it's a constant fight that I have to do.

C11: because that is usually manpower that you need for consultancy or Microsoft consultancy. So that already involves management to approve the budget.

C13: we have highly intelligent people looking at this with a nice budget so we will catch up

IT infrastructure

C1: Because it's a new setup you're installing within ASML, sir, depending on who is the approved cloud provider for ASML. So you're relying on our policy and strategy. So we were not able easily to continue with the pilot setup. And continuing with the IBM cloud environment because IBM is not, let's say, an approved cloud provider for ASML, And then you get a few struggles.

C2: We're getting a lot better with the cloud. So Cloud is being introduced to us and had a very negative stance on the cloud when I first started. But now actually, even IT provides access to the cloud. So I think it's getting better very fast.

C3: I also migrated all the development environments to the cloud, Google Cloud, because I think it was a key enabler to be successful. Without that, I don't think we could have made it.

C4: But I think cloud platforms that are outside, are in a much higher maturity state at this point. So going will also help boost building these data science products much faster.

C6: push this technology into the customers' fab. Instead of pushing them in Veldhoven infrastructure, It takes much more discussion with the customers. So either we convince our customers to share more data, or we take this technology into the customer's fab via our platform. And then we get real access to, we can really make models, who will actually work, because they are just going to be used, where they have been generated, this is what we think which so that you may call it. That's called **edge computing.** You really need both, so you need something close to you to have quick access to data and have quicker response time and then rely on the clouds for low computational products. So the combination of both in the hybrid computing is a, is what is the most efficient we are missing the edge part computing meaning the computer in the fab.

C7: So we're using the Google Cloud Platform. I don't think we have so much cooperation with internal IT infrastructure because we're going to use our Google Cloud Platform, and inside SPD, we have our own development team to develop a final product for the customer.

C8: with IT especially it is a big struggle at the moment. They don't have a lot of capacity because they don't have a lot of money.

C8: I'm using the central data center. this is on-premise.

C9: we're very actively looking at one of the things that customers have been requesting especially very large customers is GPU support.

C9: We don't use the cloud right now. Yeah and one of the reasons is because most of our customers don't use the cloud right now. An example would be, Global Foundries. I believe that they've around 100,000 CPUs that are dedicated to this processing

C10: ASML, internal IT infrastructure is based on Azure, does a lot with Microsoft Azure.

C10: so my ideal case would be a kind of local cloud, where the customer does not have access to it. There needs to be insufficient trust and confidence.

C10: Let's say, with a scalable architecture. And that would enable engineers to work on sides of themselves to develop, which will generate much faster development cycles.

C11: Microsoft Azure. Cognitive Services. and it's predominantly looking at office 365 content.

C12: And also the compute power on-site is limited. Now, that's being expanded, because it used to be, let's say only the machine itself, that had to compute power, but now we've introduced the EBS, with just the say server on-site, per machine initially and now we're moving, let's say a larger server with more compute power that can manage multiple machines at a customer site. And that's let's say the setup that we have with our major customers, but they are very reluctant, to be honest. some customers that are not willing to, Let's say have that shared approach yet.

C12: So, there, there are some logical areas where you say okay we should do that more in the cloud. But there's a quite yeah restrictive approach to the cloud if, when we talk about let's say some sensitive product data, I think, for a large part some of our companies secret documents or drawings or models or things like that cannot at the moment, still be shared to the cloud. But I think that's a matter of time.

C12: But I think now we are in many different places, very mature, and there's, of course, a lot of different areas where we still need to grow. But even the fact that we have cloud infrastructure that we are able to launch augmented reality and virtual reality like the HoloLens. There is actually quite a lot of good science that is maturing quite well in this area, I have no idea how to grade it compared to others. But the fact that we are able to securely deploy a HoloLens and 200 across the world has no major impact due to Corona, that everybody working from home, you know that shows that, from an infrastructure perspective it's very secure.

C13: I think because in research we do a lot of things locally, but then I go to the HPC(High-Performance Computing) if I really need to scale up

C14: we don't deploy anything there during install data is obtained as used in our ASML data infrastructure, so we do not deploy anything inside that was doing actual production and customer.

Competence center

C1: I think eventually as ASML, we will need to go to a situation where you have those capabilities with your own company, which makes you much more flexible, but also able to maintain the solutions yourself because you understand what is behind them.

C1: it's obviously sometimes challenging to find really experienced people because a former project manager, there's no suddenly tuning in a product owner or in a scrum master or a product, product management role. But yes, we do have those competencies all on board and working on that, and I think quite maturing already.

C1: And I think the biggest challenge for the company is going to be in the coming time is to bring them together, trying to build like an AI competence for our AI strategy or roadmap for the company. I think for internal related stuff, I think we should develop a strategy and inform architecture, involve IT all those groups to ensure that we have selected the right technology, that we have the right infrastructure, which is scalable, maintainable, those kinds of stuff. And that somehow we create a group like a competence group or competence center or capability.

C2: AI is a way to utilize the data, right? You can do analytics on the data, as well. Within the strategy, you can have a way to enable the utilization of data via AI. And could be very, very good utilization.

C3: there are some competent owners. And if you just put the core competence owners, maybe it's like 100 people, but they really are distributed heavily inside the company.

C4: there is no one unified vision everywhere, that is missing. I think now it is slowly trying to come in together from many different places and apps, they have their own authority in the league, we have their associated businesses, we have their own strategies, I think they should be unified into one ASML level strategy and then move forward. I think we are working on it. But it will take time to really have a good ASML level strategy, where we are committed at all levels.

C6: it can be a good thing to have an organization which is grouping the D&E, the research, and development into a group focused on AI in order to increase expertise

C11: So if we, if we have one global taxonomy, then it's not only important for the AI, it's also relevant for the search, it's also relevant for the mapping it to your interest

C12: we are only now starting with a roadmap approach for augmented reality and virtual reality, and we have been doing mostly experimenting up to now. So there we have a. Now slowly moving to a more roadmap approach where we do say top-down.

C13: Where do we sample, such that we can capture this distribution, and then you can start having optimal sampling strategies, Maybe optimal sample designs, what should the structure look like that'd be measured. All this needs to be taken in holistically. we need to look at that problem as one right.

Multidisciplinary team/Collaboration

C1: So we have like on the business side, so the team again, to create the product, the product owner, experts, and we have a team who is focusing on the deployment. And in my role as a project manager, I oversee that whole concept and, and responsible for everything.

C2: So there are software engineers, data engineers, infrastructure engineers, and machine learning engineers. And then there are domain experts.

C4: let's say, it's not only a machine learning solution, it is about the entire collaboration between different teams. And also the ML machine learning operations, data on production ops operation. So this part, IT comes in collaborations, collaborations like with CS.

C6: So in ASML typically we split the program. And, and D&E right in our research and development. Machine learning is not really. there is nothing that is no product at ASML at least is purely machine learning. There is always a part, of the rigorous model.

C7: we have the competence from data science from data engineering, machine learning, engineering, IT so the software development part. And of course, the business part and also involves customer support.

C8: And there I have my data preparation, and my predictive models that on a daily basis generate data, and I share that data with a diagnostic tool called TPMS. This is from customer service in different departments and the local teams all know how to use this

C8: So this data scientist, data engineer, domain expert, and software component is the flesh that you need to combine.

C10: We collaborate heavily with the functional group IDM in the device metrology group, as well as the software group that helps with the implementation. Next to that on a more global level, we have collaboration with data science groups with applied, data science group data engineering at ASML.

C11: So we work together with the people from Microsoft. my new employees started to investigate all the different opportunities and to see the applications for ASML.

C12: That means internally that we work with a lot of other departments, because they each do their bit of the whole lifecycle or the whole process, and we create, let's say the IP foundation for the product data. It's also a lot of collaboration towards the factory and the service engineers because of the foundation of data that we create for example the work instructions on how to assemble a product or how you have to do certain service actions in the field. So that's all coming from our systems, it's both IT as well as business we have quite a lot of different collaborations

C13: So I'm in research, we have an HMI project but then I kind of support and be a data science project so I'm kind of a consultant in a lot of projects. So that's, they have a project that explicitly works in HMI just supporting with ideas and patent generation, that sort of thing.

C14: we have been approached by TCS Tata Consultancy Services, which supplies Industrial analytics on a consultancy basis. So they tried to model a part of our twins can elimination, a part of our twinscan. They try to model in order that based on all calibration parameters calibration settings, calibration results. They could predict what the performance of the machine would be in the end.

C14: yes, but we can enforce expertise by a more collaborative way of working.

Agile way of working

C1: we are moving more and more towards the Agile structure. We are, let's say, teams, are built in an agile manner with a scrum master, a product owner from the business side, and a development team. Within we're trying to work according to the SAFe.

C2: I do see as the company, in D&E, for example, adapting to a more agile way of working. And that's really good that we can actually talk to a product owner of this product architect, also it safe and more flexible.

C4: We do an agile way of working. It's one of the key things.

C5: we don't completely do that in Agile because you still work with your stakeholders, they are not ready with it. So, yeah, but we, in our team, we use a Kanban board to present our use cases projects

C7: Yeah, we're working in Agile

C10: I'm not sure that safe or agile is the best way to really innovate things. safe or agile is for integrating and implementing, if you know what to do, then then it works perfectly. If you really have to innovate, I'm not sure that is the best way of organizing.

C12: Yep, we are in the middle of an Agile transformation at the moment. So is, Development and Engineering they have already done so in the past two years or so. And, but so we're just at the beginning of that way of working.

C13: Agile isn't so necessary because of people. It's easy to split the work and a lot of times we'll both write the same code because we want to learn, there's no reason to break up the functionality and do Agile for research.

C14: And we're now at the phase of validating has this brought any value to us any business value and monetary value. So I don't think we can already speak about an agile or waterfall project or are now

Employee Training

C2: But normally on I observed, like, for example, if you work with Google Cloud, Google will provide people who will train the engineers here. , it doesn't really need huge training, because the whole point of the cloud is it becomes like a self-service.

C2: Engineers normally come with competency. So if we're looking at a data scientist or machine learning engineer, they're responsible for training the machine learning model, and they normally already have the competency to train the model because yeah, then It's their job.

C4: So in our team, we have end-to-end people, not only helping the models but also deployment. In addition to that, indeed, there are some Planning to get up there ASML. To help boost some of these deployments.

C5: data analytics software. Yes, that's, that's in our plan. Because, like explained, we just had a reorganization. The business insight and control will ensure high value decision-making. So, we will provide training to either training can be the official training from the tool itself but also can be the trainee by somebody in our team to our internal stakeholders.

C7: we have tackled like we need to do a lot of knowledge sharing, training for the customer support. we have given training data to customer support so they know our product better.

C9: And so new hires go through a series of basic training and OPC and then advanced training

C11: not only employees but also content creators. So how to optimize my content for search, and AI, and how to search for relevant content. on both hands.

Business process standardization

C5: if the predictive model works. But it's requiring a structural change in their process and some changes in their process. Then, we will face some challenges.

C8: an overall data-driven way of doing business. So the numbers that you see here. I collected by calling people and getting an excel in my email. For me as a data scientist, I think, Man I'm skipping a couple of steps in maturity I'm already deploying AI to the field, but the back end, the rest of the organization, the processes behind it are still working with excel and are not automated at all. I think in the future if you want to be more cost-efficient. Then, we have a lot of legacies to fix a lot of processes to automate digitize and make sure it's dated

C8: So there's a lot of different projects, all fighting for the same memory and CPUs. IT needs to make this decision on which project to serve first. (No priority)

C8: So one of the challenges that we have is that my development environment is not the same as my deployment environments

C11: if we create a good taxonomy if we've created good content lifecycle management rules. At least we stay, we know that the content is fresher and that the AI is at least tried to process less crap.

C13: A lot of times do the ASML the processes go so fast that you don't really have calm in research, it's a little bit better, we do have, that's our task to be able to have time to think and really understand what we're prototyping. Yeah, that's what I would change, fewer processes.

C14: So there are different initiatives and everyone does it on his own way and some use Excel and some do more advanced and that's also just to pay for the data pipeline as explained. So it's also there. If our scope expands also that should grow with, that's also not centrally arranged at some point so that is also a challenge moving forward.

Data availability

C3: I think to be successful with AI, in general means that you need to have a good process for checking the quality of the data, the quantity of the data you collect, getting the right data from the system, having also a very robust software engineering environment where you can truly be agile, and it really is on a very frequent basis. AI is just one of the tools you can use.

C3: we ship a system that has not seen data. And after you've installed it, you train it on the customer data at the customer site. So we don't get the data, but the data is at the customer.

C4: sometimes it is possible that the data quality and availability are not to the standards to build a model. So we also need to see how we can consistently improve the quality and data availability.

C6: The problem is we are doing with developing tools on a limited set of data because the data is not in ASML, the data is to customer

C7: In the beginning, there are some data availability issues that will be one challenge because we need the data, from the customer.

C8: Now how much data is there available. This for me is my biggest worry. We have the sensors, but the data is still on the scanner, it's not transported to Veldhoven.

C9: No, we do face data availability problems, a lot of data ability problems. It's a general problem with the entire industry, we typically have some number of reference layouts. And we do have some trusted partners that we can get layouts from, but they very often are not entire chips and even if they are entire chips they can get very, they can be very heavily restricted on exactly what we can use them for and exactly who can see them. And that's just the nature of the game because again if a foundry ever had a data breach. They would potentially go out of business immediately.

C10: there should be a transparent policy on the issue and agreement with our customers before we can use data, and maybe we need to make a set of let's say that handles all the data in the proper way, with the proper access management that not everybody can just hop around in all the data for example

C12: Definitely. And it goes two ways, so our customers are very restricted on what data is shared. So you definitely see that in, let's say the performance data or the output of the machine data.

C13: I think we're also limited data, I mean the fab is very, very close in terms of what they're going to share.

C13: The idea is variational Bayes. So you don't need all the data you just need some of it to model the distribution then you can generate more work that we're looking into that that's kind of the new exciting research on this idea of variational Bayes. Personally, I'm very excited. I like it. And I see it, we can use it a lot because we are data-limited.

Data governance

C1: So the more formal structure there is, the easier and less time it takes to, let's say, grab the data, enrich the data for the solution and make it valuable information. If you go into let's say non supported sources, non-structured sources, which contain maybe bad **quality**, or because nobody reviews it, then it takes you much more time to establish those pipelines and set up.

C2: basically making sure we at ASML strategically, understand what is the kind of data we want to share, and what is the kind of data we want to provide better quality.

C2: I've got the data and then we can do data cleaning to improve the quality and the input for the algorithm, the algorithm.

C3: I think to be successful with AI, in general means that you need to have a good process for checking the quality of the data, the quantity of the data you collect, getting the right data from the system, having also a very robust software engineering environment where you can truly be agile, and it really is on a very frequent basis. AI is just one of the tools you can use.

C4: sometimes it is possible that the data quality and availability are not to the standards to build a model. So we also need to see how we can consistently improve the quality and data availability.

C5: they can't assure that the quality of those inputs. It's, it's not very often but it can happen.

C7: I think at this phase because we're really in the phase that we try to have the product good enough to serve the customer, and that's our biggest challenge now so we really need to find our perspective in the data quality features, the algorithm. So we need to find a way to enhance the quality and the precision to be able to reach the customer standard

C11: will definitely face quality issues, will definitely face incorrect, ownership. The prerequisite is that we clean up content.

C12: So in the design area you need to prepare your data much better so that it can be of business benefit more downstream in manufacturing or in service.

C13: A lot of times we make a lot of data and 99% of it's useless. So we have to be able to say, well, we don't need all this data. Sometimes our metrology tools, their job is to produce data. So we need to mine data for what nugget is there, and only extract that.

C13: Make sure the data is governed correctly.

C14: the Berliner Glass, used to be a supplier and now it's, it's sort of our own. But, at the beginning when it was still a supplier, also a separate initiative started to get to collect data there and to build a better data pipeline, And to discuss what kind of data format should be used.

C14: in this environment of the scanner is in the process of execution in the factory so it has thousands of inspirational factors. And the challenge is, will we be able to include all these factors into some kinds of analytics that will actually predict performance, or is it just too fuzzy and too much information that we will never be able to model actual performance.

Data platform

C1: So in our situation, we are taking information from data sources, which are not always maintained by IT. They are sometimes maintained by the business. They don't always have the right structure, we do not always know if they are properly maintained. It's much easier to set up a pipeline to get to grab the data, as a data platform and use it for indexing.

C2: Not every product needs to use 2000 data sets, maybe now these five data set can make this product a lot better. And my job is basically to manage the data portfolio in that, hey, currently we are using this time we will not be using this country we're sharing this country we're not sharing this and that's the job for selecting this data, the data flow I think within ASML and make sure the ownership of it with the right person.

C3: I invest first in making sure we go to the clouds to have a very fast release cycle. And then you can prove that AI works. But if you focus first on the algorithm, and forget about all the rest, you just will not be successful.

C4: the data center platforms, they are really key for innovation, or let's say they are really key to land our data sets for us, was one of the biggest challenges. in ASML, services are scattered all around. So it's not good to build this data-driven product, it takes a lot of time to build a product and then give it to a customer lab to create value out of it. Right. The point we need a really good data sets platform.

C8: I think there's a big room for improvement in the strategy, so I need a platform, I need tools to augment those models, and I have to have to redesign them and pull them myself.

C8: But there are the data ideas be trying to build more for six months and it doesn't work, it has the same platform and scalability issues as before.

C12: Let's say data analytics platform, and the machine data platform that's in that's mixed. So there I think we have restricted access to our customer and I think it's also even a commercial agreement, how much access they get to that. And of course, if they pay for that service or if they have then they get proper training and proper access that they can actually use it

Explainable AI with domain expert

C1: And on the other hand, you obviously need to be lucky that the topic is something which they know something about.

C2: probably the more important part is finding, finding the right problem to solve. That requires a really strong understanding of the domain of ASML, the domain of customer, and also the whole science scientific, that's really the science, the core, you know, really get in-depth detail of the lithography. And those people are very rare, or the combination of these activities happens very seldom. So they are probably, yeah, we rely a lot on senior people. But there, it would be a lot better. If we had more, more, more interesting ways of doing it, I don't know what that is, this is something we could really improve a lot on.

C3: But I don't want to take out of fab, then it becomes a lot more difficult because machine learning systems by design already are difficult to troubleshoot because they learn but it's difficult to grasp what's going on there. But if on top of it, the customers don't give you the data, you need to troubleshoot it, it becomes very difficult to maintain. And I think this is a big roadblock that we have to workaround. And that is also very dependent on the customer.

C4: At the same time combine the domain knowledge in a very nice way. So that the algorithm which you've created is there's also going to work for other questions as well. So we have some IP here.

C5: Yes, that refers to explainable data science, data modeling something like that. And also, more commitment from the business side, and also their knowledge in terms of data, analytics, data science.

C6: Only if you really know what's happening inside of the scanner, and that is intellectual property, the intellectual property is what can really improve and increase the development of machine learning models. And we, ASML has decent intellectual property

C7: There are domain experts from different departments actually, because we're like the data science part, they're the knowledge domain expert. so domain knowledge is very important because that's how features are for machine learning and the idea of modeling. And we also have local customer support in beta customers, so they can also have us go to the factory to get the report to give us an idea, what could be improved for the further steps.

C8: success is when we have domain experts from the function clusters that know all about the part that we want to model.

C9: And so at that point, if they see a marginality they need to be able to know Was this on something that was trained on or wasn't trained on and what specifically can they do about it is the problem on their side, or is the problem in our software, things like that this is extremely important to them. And this can be a real, a real issue with them with respect to adoption because you know they can see really good results on everything that they have tested, but their worry is about things that they, that they can't foresee coming.

C9: that particular problem with neural networks and with machine learning, in general, it's a very different problem because again the black box that we talked about before becomes problematic question is, do you have to rebuild your model and if you rebuild your model, to fix this particular hotspot

C10: If you want to develop and improve certain technology, you need to understand what happens if you don't understand then you don't know how to improve.

C10: You can put those physical restrictions at a much higher abstraction. and that makes the model more smooth, more adaptive to the experimental situation

C13: so I do want to understand the processes and how physically these things work. I do think that helps in designing what the model should look like.

C13: we might be able to outsource that with our domain knowledge with our data and build something like maybe with an IBM Watson, something like that

C14: What should the limits be which parameters to monitor that's all based on simple selection and domain expertise now

Context-aware AI modeling

C1: Still ASML. I mean, we have documents with spelling mistakes, we have no comments, it's very technical language. And for all those things, you will need to build your custom entity model and then link those entities, how do they relate to each other? And based on that building ontology, and currently, we are doing that. So the engineers, let's say the experts are creating that together with IBM, like a collaboration with the supplier, we are providing the **context** behind the information and providing information on what would make sense. And IBM is then helping us to structure that and making like a model out of it.

C1: But if you are talking about ASML, that's the technical slang and our message structured and unstructured documents, you will need to build this custom entity model besides this already available model.

C4: And specifically, the biggest challenge in ASML is our products keep changing. So they are always consistently constantly changing. Because we always innovate and create the new little innovation. How do you make sure that the machine learning algorithm, which you will create for a product A will also work for a dot one, the new version of that is, we need to reinvent ourselves.

C4: you also need the context information, like what happened to the customers. Did the customer do some services, was there a service engineer was there some repair done, this information is really key, but it is very limited. Your models should be sharp enough to do to deal with these challenges. The notion that our datasets are small, limited, varying products, is funny, actually, we have really big data sets, but it is less variety.

C7: because if you have data from too many small contexts is also impairs the precision. So, context is true quite a tricky issue.

C7: So we are able to have a lot of parameters, we can tune to make it more specifically for the specific customer. So we cannot make a ready product just for the customer we need to make sure it's flexible in a way we can still fine-tune it

C10: On the other hand we hope for it that it's more generic than just for one layer for one customer.

C11: We can also find discovery for advanced mining gamification semantic search in various contexts because context is important

C13: we design it based on, maybe some mass balance constraints, maybe some optical imaging type of constraints, we take those into mind we are context-aware. It's not just, yeah, here's some data regress and goes. I do think context-aware models are very important, and that's what we make. We don't just plug in Jack.

Model operation

C2: So, within the team, there is the data scientist role, there is an engineering role, and an ML engineering role. So what needs to be taken care of for productizing? That AI that's basically taken care of by the ML engineering role.

C3: So you don't want to start from scratch, you typically, what you would ask the customer is, before you install the system, please store as much historical data as possible. And then the tool can start so it just goes faster to learn. So for me, the best way to scale is basically accepted that your tool will need a bit of a learning curve, once deployed customer site and making sure that it gets the right data and the high quantity of data once deployed. And then it keeps on learning.

C6: Now the problem we have is being in the fab we can maybe not access the internet can maybe not access all the features of Google Cloud

C7: So, our product we have two environments, one is a development environment and one is a production environment so our development environment is on GCP, google platform. And for the final product, it's a standalone software that aims to be deployed at customer sites.

C7: the second one is we have a kind of performance diagnostic report. we don't see the data but we do get the report the Performance Report, which we do know how performance is and maybe a feel where it could go wrong. And that gave us a clue how to make it to how to improve with further steps

C8: we have the competence to build these AI models, deploying them automating them is quite challenging. Getting the Model is, that they should, but the easy part. But making that model, Getting us going, and more so that on a daily basis generates the model outputs, and share that with all the local teams. That's a lot of software quite complex.

C9: If a company has no problem with our software, they don't tend to tell us that things are going great, they just don't say anything, if things do go, if they see a problem, then they say, here's a problem and we need you to fix it, they very often don't give you enough information to be able to reproduce the problem.

C13: my background is control theory so in my mind I'm always thinking in terms of a state. So you have the projection that's learned, and then all it's changed is the state that defines the projection is drifting, so you can use the sole, that same model but you have an estimate of where you are in the space that you're operating in. So I always try to build these things with the concept of having a state of the system

Peer companies/competitors/software vendors

C2: there is a competitive landscape. And in the competitive landscape, a lot of our application competitors do have a lot more AI products than us. So the pressure is more like, by not doing anything, are we missing out? And we can definitely do more. So let's see if we have more products.

C5: We learn from our peer companies like Philips, or some other industrial company like Vanderlande, what they are doing in their finance department.

C9: every EDA company is pursuing, and I believe every EDA company has some sort of product that's associated with machine learning right now.

C10: So if our main competitor is KLA, they have been in the market, a long time, dominating there with their overlay products, they did not really improve a lot each time until we came on the market and we provided new concepts, etc. that worked faster, better, more precise. And now they feel the pressure of ASML, and they are starting to improve themselves so that you could easily consider that a healthy competition and say they are challenged to make their own product also better.

C11: We're actually earlier than most companies I collaborate with Because I'm part of a Dutch consortium with like Philips shell DSM X or Nobel, all these kinds of companies. And now we're, we're pretty far into this. Because in most of the companies, the only sector all these platforms and the surety Cetera lies within IT. And there's not enough business push for this. If there is no top-down business push, and there is no bottom-up because IT is too busy making sure that the current requirements are done rather than bringing an issue in ASML, we have something in between, we have to business, to push IT to come to a bottom of the thing.

C12: we also get, let's say, technology push from vendors that we work with either software vendors or consulting firms that think there's an opportunity there.

C12: But from an IT perspective, I have not felt any pressure from let's say, Applied Materials, or other kinds of, let's say, semiconductor companies that they are ahead, we sometimes do actually talk to them. When we go to a conference or sometimes even have dedicated meetings. And then you do see a little bit, how you're comparing and, and also that you can let's say take away their best practices like they also learn from us.

Customer demand

C1: In this project, there is no cost customer involvement. Also, no pressure from the customer. Because this is our internal, our internal processes. But obviously, there's always the pressure of the customers to ensure that issues, if they encounter, are being fixed. So whatever we built here somehow relates to the customer

C3: time to market is related to them in the time engineers need to deliver a solution. So, this is where you also need to have a very good understanding of the time the activities where they spend most of their time and they do value chain mapping is okay. So AI can just be very clever at selecting the test cases to qualify solutions to still deliver quality, but without taking too much time.

C3: So what is the tradeoff between the quality of what I deliver and the time to delivery of the systems. An engineer there will be more looking into those to do machine behavior optimization because you see that the machine is operating typically in a customer environment where they don't always control everything. So they want to make sure that when They do ship a system, it can optimize its behavior to the customer environment. And this is an area where AI is typically very good at.

C6: Intel TSMC Samsung Hynix, and they are asking for our help because they know that they cannot they just can go so far if they don't have our knowledge they need to step up and this is why we're engaging more and more in tools such as scanner performance detection

C8: We started predictive maintenance one and a half years ago, there was a request from a customer as well. Samsung, Intel, they're very interested in predictive methods.

C9: One of the reasons why OPC is so important to foundries, just to give you a bit of background is, it's the very last step of design it's called Design finishing the very last step of the design before you start ordering masks and then those masks, go to a mask shop, they create these reticles these masks, and they bring them back into the foundry, to start creating the chips themselves

C13: Our biggest competitor was the fab. The fab was just like oh we can do this ourselves, gives us access to this data will make the controller. And it's hard to beat, ASML had the same problem where they just say give us access to these images, and they will make their own analysis. So we have to build something that they want to use in terms of AI that they can't just go to. And that takes thought.

C13: we have to protect ourselves that it's not copied that scale, but it has to add value. That's simple.

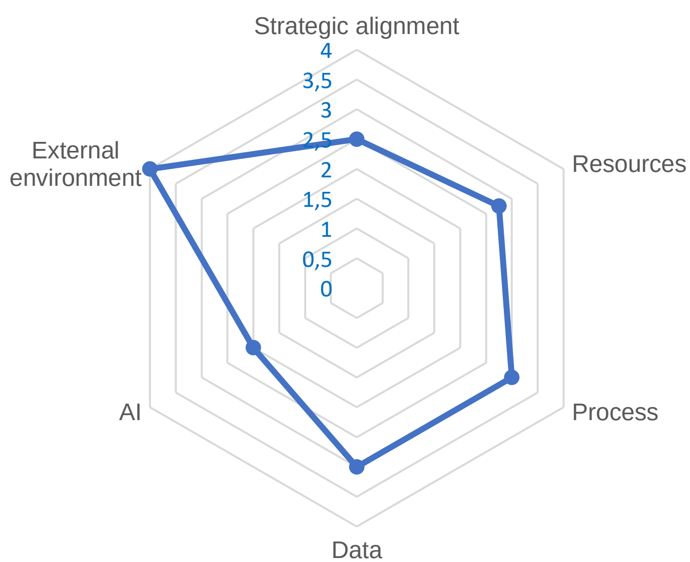
C14: if you look at it, business-wise, we are really pushed by our customers. They really are asking us for years already, to do SPC, and also do more SPC and even more SPC. So they really asked to progress. , there is a drive from the customer point of view

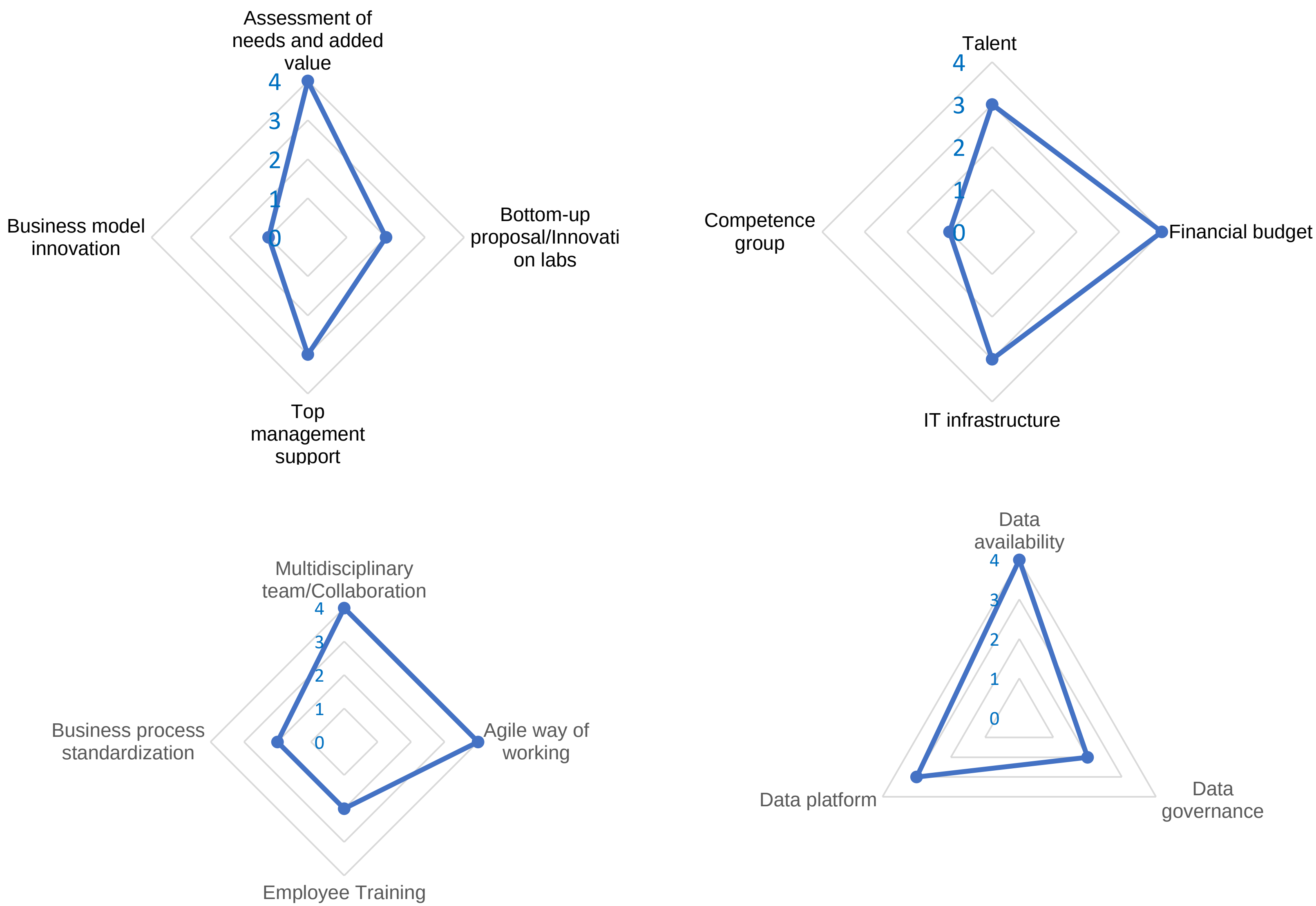
Appendix H: Example use of the framework

A score range from 1-5 is first given to evaluate each readiness factor by referring to Table 10 with a scoring description. Then the average score of 20 readiness factors is calculated to determine the level of AI organizational readiness. For example, the average score in this example organization is 2.8, thus the readiness level is AI starter (1.1-3) and is close to reaching AI-ready (3.1-4). After the assessment, the organization can have a better understanding of their current AI capability in different dimensions and specific readiness factors. The factor with a low score should be focused on for improvement.

Dimension	**No.**	**Readiness factor**	**Assessment**	**Score**
Strategic alignment	1	Assessment of needs and added value	The organization can identify suitable AI use cases that provide added business value. The organization views AI as a tool to solve problems.	**4**
	2	Bottom-up proposal/Innovation labs	The organization encourages employees to innovate and propose potential improvement points. The innovation lab, hackathon, workshop, etc. are held.	**2**
	3	Top management support	Management support is in place to allocate necessary resources.	**3**
	4	Business model innovation	The organization takes business model design into consideration that best fits the targeted AI application/product.	**1**
			Score	2.5
Resources	5	Talent	The organization has a certain number of talents with AI and industry expertise that ensure the model development.	**3**
	6	Financial budget	The budget is sufficient for all kinds of activities around building AI solutions.	**4**
	7	IT infrastructure	The organization has appropriate and adequate IT infrastructure to support the model training and development.	**3**
	8	Competence group	To build in-house AI capability, the organization recognizes the importance of knowledge management to centralize AI skillsets and learn from experience.	**1**
			Score	2.75
Process	9	Multidisciplinary team/Collaboration	The multidisciplinary team is composed to facilitate AI development. Collaboration across departments can be achieved if necessary.	**4**
	10	Agile way of working	The organization adopts an agile way of working to have fast development cycles.	**4**
	11	Employee Training	The organization provides employee training with necessary AI skills.	**2**
	12	Business process standardization	The organization establishes clear and standardized business processes to avoid redundant work and enable the integration of AI applications.	**2**

			Score	3
Data	13	Data availability	The organization gains an adequate amount of data for the model development.	**4**
	14	Data governance	The organization can ensure the quality, clear ownership, security of the data.	**2**
	15	Data platform	An appropriate data platform is there to reduce the complexity of development.	**3**
			Score	3
AI	16	Domain expertise for explainable AI	The organization has domain experts with a deep understanding of the application to determine the feature of the model and make it more explainable.	**3**
	17	Context-aware AI modeling	The model can be adaptable to a variety of situations. It has a self-learning ability to work in different contexts and improve its performance over time.	**1**
	18	Model operation	The organization can manage the model throughout its lifecycle in business.	**2**
			Score	2
External environment	19	Peers/competitors/software vendors	The organization learns from its peers, competitors, and other vendors to track the market dynamics in AI applications and keep competitive in the market.	**4**
	20	Customer demand	The organization understands the customer demand and makes improvements.	**4**
			Score	4
			Average score	2.8




Assessment of needs and added value
Bottom-up proposal/Innovation labs
Top management support
Business model innovation
4
3
2
1
0
Talent
Financial budget
IT infrastructure
Competence group
4
3
2
1
0
Multidisciplinary team/Collaboration
Agile way of working
Employee Training
Business process standardization
4
3
2
1
0
Data availability
Data governance
Data platform
4
3
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1
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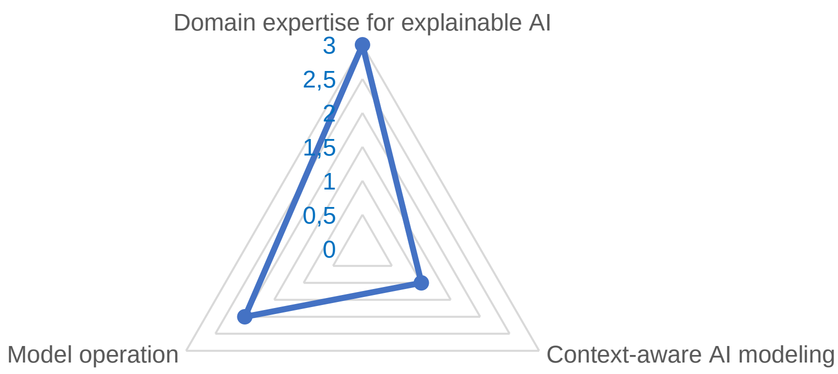

Radar charts can be made for users to visualize an organization’s readiness level in each dimension and each factor in one dimension. Such charts can help users realize the strengths and weaknesses of the organization. After the assessment, the organization can determine its target level and put the effort into improving certain factors. This qualitative study does not give weight to each dimension or readiness factor. It calculates the average score in the assessment. A quantitative method can be used in the future to establish the weights of the dimensions or factors and to determine their priority for tasks under the improvement plan.