Exploring the Role of Digital Technologies in Business Model Changes of Renewable Energy Firms in the Netherlands

MOT2910: Master Thesis Project

Prithvi Kalpesh Thakkar

Exploring the Role of Digital Technologies in Business Model Changes of Renewable Energy Firms in the Netherlands

by

Prithvi Kalpesh Thakkar

Student Number: 6017215

First Supervisor:	Prof. Dr. Hanieh Khodaei
Chair & Second Supervisor:	Prof. Dr. Roland Ortt
Advisor:	Ghassan Kharbeet
Project Duration:	March 2025 – July 2025
Faculty:	Technology, Policy and Management

Delft University of Technology

Preface

When I began my Master's journey in the Netherlands, my only goal was to try something new, and it turned out to be one of the most challenging yet rewarding decisions of my life. Everything was unfamiliar at first: the place, the culture, the people, and even the academic structure. But with every new experience came growth. These years have shaped me not only as a professional but also as a person, teaching me adaptability, perseverance, and the value of keeping an open mind. This thesis marks the culmination of that journey, and I would like to express my deepest gratitude to those who have guided, supported, and inspired me along the way.

I am sincerely thankful to my supervisors, Dr. Hanieh Khodaei, for her continued guidance and for always pushing me to do better, and Prof. Dr. Roland Ortt, for his valuable and detailed feedback that consistently challenged me to raise my work to a higher standard. My appreciation also goes to my PhD advisor, Ghassan Kharbeet, for his constant support and willingness to help whenever needed. I am also grateful to my thesis committee for encouraging me to write a research paper, which turned out to be a truly rewarding experience. For someone who never had a strong interest in research, this became an important learning milestone and a journey I am glad to have taken.

I would also like to thank all the companies that generously participated in my interviews. Their time, openness, and insights made this research possible and enriched it in ways that would have been difficult to achieve otherwise.

Smit and Tango have been my biggest constants since childhood. Thank you for always guiding me, standing by me, and inspiring me to take on new challenges with confidence.

To Geeta and Kalpesh, for believing in me unconditionally. To Jiyanshi, Ishita, Darshana, Ankit, Arti fui, Jasmina maasi, Nihar, Parth, Rhea and my entire family, thank you for being my biggest cheerleaders.

To my SBS brothers, Nihal, Harsh, Sid, Adit, Abhi, Rohan, Kushal, and Bhavya, you have been with me through every stage of life. To Mihir, Priya, Manas, Diya and Krisha thank you for always keeping in touch despite the distance.

To Riya, thank you for your constant encouragement, for believing in me during the tougher moments, and for reminding me to stay patient and focused. I have truly valued sharing this journey with you. To Harsh, Sid, Nihal and Pooja, thank you for motivating me, believing in me, and always having my back, no matter the distance. You all have always been just a call away.

To Vidhi, Anuj, Jabez, Anurag, Bhavesh, and Sanjana, thank you for being my constants in the Netherlands. To Sayak, Shubham, GG, and Komal, I am grateful for all the good times we have shared here.

I am deeply grateful to ORT_ and Vikasit Bharat Group, with whom I gained invaluable experience and which continues to be a big part of my life, and to everyone there who has supported and encouraged me over the years.

As this chapter comes to a close, I look forward to the opportunities and challenges that lie ahead. TU Delft has shaped me in countless ways, and I will always carry the lessons and experiences with gratitude.

Prithvi Thakkar
Delft, August 2025

Executive Summary

The digitalization of the energy sector is accelerating, with renewable energy firms increasingly adopting technologies such as artificial intelligence (AI), Internet of Things (IoT), blockchain, and digital platforms. While the technical potential of these tools has been widely studied, less is known about how they strategically transform business models, particularly in high-tech renewable energy firms operating in dynamic, innovation-driven environments. This thesis investigates how digital technologies drive business model change in such firms, with a focus on the Dutch renewable energy sector.

The central research question is: **How do digital technologies drive changes in business models for high-tech firms in the renewable energy sector in the Netherlands?**

To address this, the study explores three areas:
1. which digital technologies are most influential,
2. how these technologies affect the core components of business models: value creation, value delivery, and value capture, and
3. how business models evolve over time in response to digitalization.

To answer these questions, the thesis adopts a qualitative, exploratory approach combining a Systematic Literature Review (SLR) with semi-structured interviews. The SLR analysed 29 peer-reviewed academic papers published between 2015 and 2025, while the empirical component involved five interviews with professionals from Dutch high-tech renewable energy firms actively engaging with digital innovation. Both datasets were analysed using the Gioia methodology, enabling structured coding of observed digital applications, patterns of change, and their relation to business model components. The analysis was guided by established frameworks of business model change - Adaptation (BMA), Evolution (BME), Innovation (BMI - and interpreted through the lens of Business Model Dynamics (BMD).

The study identifies five functional roles through which digital technologies influence business models:
1. Data Capture & Embedded Infrastructure (e.g., IoT, smart sensors)
2. Data Processing & Intelligence (e.g., AI, digital twins)
3. Trust & Coordination Infrastructure (e.g., blockchain, smart contracts)
4. Customer Interface & Engagement Platforms (e.g., cloud dashboards, mobile apps)
5. System-Orchestration & Ecosystem Tools (e.g., virtual power plants)

These technologies often operate in combination, forming digital stacks that cut across business functions. Analysis shows that value creation was the most significantly transformed component, firms leveraged digital tools to automate operations, shorten development cycles, and deliver new data-driven services. Value delivery evolved through personalized platforms, integration with partner services, and interactive customer channels. Value capture, while showing less transformation, included emerging models such as tokenized revenue streams, energy-as-a-service, and usage-based pricing enabled by digital infrastructure.

In terms of business model change types, the findings reveal Business Model Adaptation (BMA) often emerged as a response to contextual constraints (e.g., offline modes in low-connectivity regions or regulatory adjustments). Business Model Evolution (BME) was the most prevalent change type, characterized by layering digital tools to incrementally enhance existing activities and expand capabilities. Business Model Innovation (BMI) occurred in select cases where firms deeply integrated digital tools across the entire business model, enabling new value logic and revenue mechanisms.

This study finds that these change types do not occur in isolation or follow a linear path. Instead, firms exhibited coexisting patterns of adaptation, evolution, and innovation, sometimes simultaneously in different parts of the business. This supports a Business Model Dynamics (BMD) perspective, where digital transformation is seen as cumulative, non-linear, and dependent on both internal strategy and external conditions.

Key theoretical contributions of this research include the functional grouping of digital technologies, complemented by a layered conceptual view of this stack, and the introduction of the concept of digital integration depth, defined as the extent to which digital technologies are structurally embedded across business model components. The study suggests that deeper integration correlates with more transformative outcomes (i.e., BMI), while shallow or siloed use typically results incremental BME. This framework helps explain why firms using similar technologies experience different degrees of business model change.

The thesis concludes that digital technologies are indeed reshaping business models in the renewable energy sector, predominantly through evolutionary rather than disruptive shifts. By illuminating how and why these changes occur, the study contributes to a deeper understanding of digital business model change and offers both theoretical and practical insights.

Theoretically, it expands the application of BMA/BME/BMI frameworks to digital contexts and proposes digital integration depth as a potential explanatory lens for business model outcomes. Practically, it provides guidance for firms seeking to navigate the energy transition: to move beyond isolated tool adoption and invest in more strategic, cross-cutting digital integration to unlock new business model potential.

Table of Contents

List of Figures

List of Tables

Nomenclature

Abbreviations

Table 1. List of Abbreviations

Abbreviation	Full Form
AI	Artificial Intelligence
API	Application Programming Interface
BMA	Business Model Adaptation
BMD	Business Model Dynamics
BME	Business Model Evolution
BMI	Business Model Innovation
BM	Business Model
DTP	Digital Technology Platform
IoT	Internet of Things
ML	Machine Learning
P2P	Peer-to-Peer
RE	Renewable Energy
SaaS	Software as a Service
SLR	Systematic Literature Review
VPP	Virtual Power Plant

1 Introduction

1.1 Background and Context

The transition toward renewable energy (RE) is not only reshaping the global energy landscape but also prompting deep changes in how firms operate, deliver services, and remain competitive. As decarbonization pressures intensify, particularly for high-tech renewable energy firms, the sector is undergoing transformation that is not solely technological, it is also strategic. Firms are being compelled to reconsider their organizational structures, customer relationships, and revenue mechanisms in response to new energy architectures and market expectations (Foss & Saebi, 2017).

A business model is commonly defined as the structure through which a firm aligns its resources, activities, and creates & delivers value for customers while trying to achieve competitive advantage (Osterwalder & Pigneur, 2010; Teece, 2010). Foundational work in this area has emphasized that business models are not static but reconfigurable systems of interdependent elements (Zott & Amit, 2013; Chesbrough, 2010). In dynamic contexts such as the energy transition, firms may pursue changes to their business models along multiple paths: through short-term adaptation, longer-term evolution, or more radical innovation. These paths are captured under the broader concept of Business Model Dynamics (BMD), which describes how business models are continually adjusted in response to environmental changes, digital opportunities, and internal learning (Khodaei & Ortt, 2019; Foss & Saebi, 2017). Within this framework, Business Model Adaptation (BMA), Business Model Evolution (BME), and Business Model Innovation (BMI) represent different types and degrees of change.

As the energy sector shifts from centralized fossil-based production to decentralized renewable generation, these technologies are becoming essential to manage variability, grid integration, and end-user participation. Digital technologies have emerged as key enablers of the transformation. Technologies such as artificial intelligence (AI), the Internet of Things (IoT), blockchain, and cloud infrastructure are playing an increasingly important role in managing complexity, forecasting energy production, automating planning and operations, enhancing traceability, and improving customer engagement (Gitelman & Kozhevnikov, 2023; Leiva Vilaplana et al., 2025). These developments are also challenging the traditional utility model and encouraging firms to adopt more data-driven, participatory, and customer-oriented business structures (Franki et al., 2023).

However, the adoption of digital technologies is not merely an operational upgrade. It often results in a deeper reconfiguration of the firm's value logic, changing how it creates, delivers, and captures value(Trischler & Li-Ying, 2022; Hu et al., 2022). Business model innovation has been widely examined in the context of sustainable and digital energy transitions (Geissdoerfer et al., 2018; Gitelman & Kozhevnikov, 2023; Leiva Vilaplana et al., 2025; Neska & Kowalska-Pyzalska, 2022), reflecting how firms in the renewable energy sector increasingly adopt new value logics to respond to digitization and decentralization. Recent evidence suggests that while some firms are layering digital capabilities over time, others are adopting entirely new business logics via decentralized platforms or multi-service digital ecosystems (Leiva Vilaplana et al., 2025; Gitelman & Kozhevnikov, 2023; Neska & Kowalska-Pyzalska, 2022). Yet in the renewable energy sector, limited empirical insight exists into how firms differentiate between adaptation, evolution, and innovation trajectories driven by the adoption of digital technologies.

This thesis responds to this gap by exploring how digital technologies influence business model change in high-tech renewable energy firms in the Netherlands. It aims to clarify how high-tech renewable energy firms perceive and implement business model change in response to digital technologies, whether through short-term adaptation, incremental evolution, or radical innovation, and how these digitally enabled changes unfold as part of broader business model dynamics. The Dutch context offers a particularly relevant empirical setting given its active experimentation with blockchain-enabled peer-to-peer trading, digital energy platforms, and collaborative smart grid pilots (Neska & Kowalska-Pyzalska, 2022; Leiva Vilaplana et al., 2025). Moreover, as this study is conducted from within TU Delft, an institution embedded in the Netherlands' innovation ecosystem, it provides proximity and access to digitally active renewable energy firms, facilitating direct engagement with relevant stakeholders. By doing so, this study contributes to both academic and practical understanding of strategic responses to digitization in the renewable energy sector.

1.2 Problem Statement

Despite the growing interest in digitalization within the renewable energy sector, much of the existing research continues to emphasize the operational benefits of digital technologies, such as automation, remote monitoring, and energy forecasting, rather than their strategic implications for business model transformation (Gitelman & Kozhevnikov, 2023). Digital tools like AI, IoT, and blockchain are increasingly deployed across various stages of the energy value chain (Muhammad Adnan et al., 2024; Pakulska & Poniatowska-Jaksch, 2022), yet the ways in which these technologies influence a firm's business model, particularly in terms of how value is created, delivered, and captured, remain empirically underexplored (Gitelman & Kozhevnikov, 2023).

Foundational studies have introduced valuable frameworks for understanding business model innovation and business model dynamics (Foss & Saebi, 2017; Khodaei & Ortt, 2019). However, few empirical studies examine how digital technologies specifically trigger different types of business model change, such as short-term adaptation, incremental evolution, or radical innovation. Most literature treats digitalization as a general enabler of innovation in the renewable energy (and more broadly the energy sector), without detailing how firms perceive or operationalize distinct trajectories of transformation.

What remains underexplored is how firms interpret and enact digital technology adoption as a trigger for business model change (Malewska et al., 2024). This lack of clarity limits our ability to conceptually and practically understand the role of digital technologies in shaping business model changes within the renewable energy sector. Moreover, the outcomes of digital integration are not homogenous across firms. Some may enhance existing models through digital augmentation, while others may develop entirely new configurations, resulting in novel service architectures, partnerships, or monetization strategies. This heterogeneity highlights the need to explore business model dynamics (BMD), focusing on the patterns, scope, and strategic depth of changes across business model components during digital transformation.

Empirical research on this topic is especially scarce in the context of high-tech renewable energy firms, startups and digitally oriented companies that are often at the forefront of innovation. While large utilities and community energy pilots have been studied (Del Vecchio et al., 2025; Mika & Goudz, 2021; Neska & Kowalska-Pyzalska, 2022), there is limited understanding of how smaller, agile firms respond to digital opportunities in real time. This is particularly relevant in the Dutch context, where policy, digital infrastructure, and innovation ecosystems actively support experimentation with new business models and technologies (Leiva Vilaplana et al., 2025).

This study aims to address this gap by examining how digital technologies shape business model innovation in high-tech firms operating within the renewable energy ecosystem, including firms developing enabling technologies, products, or platforms.

1.3 Research Objective & Scope

The overarching objective of this research is to investigate how digital technologies drive business model change in high-tech firms operating within the renewable energy sector. This includes firms engaged in the development of energy-related innovations, digital platforms, and renewable energy technologies. Although digitization is widely acknowledged for improving operational efficiency, its strategic role in shaping business model changes remains underexplored in both academic and practical domains.

The scope of this study focuses on high-tech firms in the Netherlands and Europe more broadly that are actively integrating digital technologies within renewable energy contexts. This study seeks to bridge this gap by identifying the key digital technologies shaping the renewable energy landscape. These include technologies such as Artificial Intelligence (AI), Internet of Things (IoT), and Blockchain. It then analyses how these technologies impact the foundational components of business models: value creation (e.g., product/service innovation, customer engagement), value delivery (e.g., channels, partnerships), and value capture (e.g., revenue models, cost structures). Ultimately, the study aims to explore how digital technologies shape business model dynamics by examining the types of changes that occur and the specific components they impact.

1.4 Research Question and Sub-Questions

This research is guided by a central question aimed at understanding how digitization is reshaping the strategic core of high-tech firms in the renewable energy sector:

Main Research Question

How do digital technologies drive changes in business models for high-tech firms in the renewable energy sector in the Netherlands?

To address this overarching inquiry, the following sub-questions are posed:

1. **What are the key digital technologies influencing business models in high-tech renewable energy firms?**
   This question aims to identify key digital technologies such as Artificial Intelligence (AI), Internet of Things (IoT), Blockchain, and others that go beyond operational

optimization and are used more often in the renewable energy sector. It evaluates their role in reshaping core business model components-value creation, value delivery, and value capture.

2. **How does digitization impact the individual components of business models-value creation, value delivery, and value capture-in these firms?**
   This sub-question explores how the above identified key digital technologies affect the development of new value propositions, alter customer engagement mechanisms, reshape delivery channels, and influence monetization strategies in high-tech firms within the renewable energy domain.

3. **How do business models evolve over time in response to digitization in high-tech renewable energy firms?**
   This question investigates whether the integration of digital technologies leads to incremental adaptations, comprehensive transformation of existing business models, or the emergence of entirely new models. It seeks to uncover patterns and degrees of business model changes through the identified digital technologies.

Collectively, these questions are designed to uncover how digital technologies act as drivers of change across the core components of business model in the renewable energy sector. By focusing on high-tech firms in the Netherlands, the study ensures contextual specificity while contributing to broader theoretical and practical discussions on business model innovation under digitization.

1.5 Methodology Overview

This research adopts a qualitative, exploratory approach to investigate how digital technologies drive business model change in high-tech firms operating within the renewable energy sector. Given the multidimensional nature of the topic, spanning technological, organizational, and strategic domains, a qualitative design enables the collection of rich, contextual insights that are grounded in expert perspectives.

The empirical component of this study is based on semi-structured interviews with senior professionals from selected high-tech renewable energy firms in the Netherlands. These firms were selected through purposive sampling, reflecting diverse approaches to digitalization within the renewable energy sector. The sample includes organizations engaged in the development or application of enabling digital technologies such as AI, IoT, blockchain, and digital platforms.

To analyse the interview data, the study employs the Gioia methodology (Gioia et al., 2013), which supports inductive theory development through a systematic coding process. The analysis proceeds from first-order concepts (informant-centric terms), to second-order themes (researcher-centric interpretations), and finally to aggregate dimensions. This structured approach ensures analytical rigor while allowing theoretically meaningful patterns to emerge. A parallel Gioia-based coding strategy was also applied to the Systematic Literature Review (SLR), enabling alignment between conceptual insights from prior research and empirical findings from interviews.

By combining insights from both literature and expert interviews, the research aims to identify key digital technologies, examine their impact on business model components, and analyse patterns of business model adaptation, evolution, or innovation across different firms.

1.6 Academic and Practical Relevance

The academic relevance of this study lies in its contribution to the growing but still underdeveloped body of research on business model change, including adaptation, evolution, and innovation, in the context of digital transformation and the energy transition. While digital technologies have been widely studied for their technical and environmental benefits, their influence on strategic business dimensions remains insufficiently explored, particularly through empirical, interview-based research with professionals working inside high-tech renewable energy firms. By applying the Gioia methodology, this thesis contributes conceptually grounded insights into the nuanced ways digital technologies interact with business model components, offering a good understanding of business model changes in a dynamic and rapidly evolving sector.

Practically, this research aims to help high-tech renewable energy firms reflect on how digital technologies, such as AI, IoT, blockchain and others, can be applied to adapt or transform their business models. Initial patterns suggest that these technologies are often used to enhance value creation, while more fundamental business model transformation remains limited. As the study progresses, it will offer insight into how different approaches to digitization correspond with varying levels of business model change, providing useful direction for practitioners, policymakers, and investors aiming to support innovation in the sector.

This thesis draws directly on the author's academic journey in the Management of Technology program at TU Delft, where innovation, entrepreneurship, and digital transformation were central themes. Research Methods provided the basis for formulating research questions and designing a qualitative study, while Technology Entrepreneurship and Innovation and Digital Technology Entrepreneurship and Management deepened understanding of high-tech business model development and the role of AI, IoT, blockchain, and other emerging technologies in shaping competitive advantage. Emerging and Breakthrough Technologies offered perspective on the lifecycle and diffusion of high-impact technologies, and Technology Strategy and Entrepreneurship strengthened the strategic lens for assessing their integration. Together, these courses equipped the author with the conceptual foundation and methodological skills to analyse how digital technologies influence business models in high-tech renewable energy firms.

1.7 Thesis Structure Overview

This thesis is organized into six chapters, each building on the previous to examine how digital technologies influence business model changes in high-tech renewable energy firms. Chapter 1 introduces the research, outlining the background, problem statement, objectives, questions, methodology, and relevance. Chapter 2 introduces key concepts in relation to the thesis and discusses prior research and literature on digital technologies & business model changes in the renewable energy sector to establish the theoretical foundation for the empirical phase. Chapter 3 details the qualitative methodology, including SLR, semi-structured interviews and the Gioia coding approach. Chapter 4 presents the SLR and empirical findings, structured around business model components and coded insights. Chapter 5 discusses these results in relation to with each other(theory and practice), while also addressing limitations. Chapter 6 concludes the thesis by summarizing contributions and offering recommendations for future research.

2 Conceptual and Literature Foundations

The accelerating shift toward a low-carbon economy has positioned renewable energy at the centre of both technological and strategic transformation. As global efforts to decarbonize intensify, energy systems are not only being redesigned from a technical perspective but are also prompting firms to rethink how they operate, compete, and create value. While much attention has been devoted to innovations in generation, storage, and grid management, there is growing recognition that digital technologies are enabling deeper and more strategic shifts within firms, reshaping the core logic of their business models (Gitelman & Kozhevnikov, 2023; Trischler & Li-Ying, 2022; Hu et al., 2022).

Technologies such as artificial intelligence (AI), the Internet of Things (IoT), blockchain, and others are increasingly used to automate operations, personalize customer engagement, enhance forecasting, and facilitate decentralized energy transactions (Ahmad et al., 2021; Adnan et al., 2024; Hu et al., 2022). However, the influence of these technologies extends beyond efficiency improvements. In many cases, they trigger a need to reconfigure how firms create, deliver, and capture value, prompting various degrees of business model change (Franki et al., 2023; Singh et al., 2021; Malewska et al., 2024). Some firms may respond with adaptations that incrementally refine existing components (Business Model Adaptation, or BMA), while others may undertake more systemic changes that reflect Business Model Evolution (BME) or even full-scale Business Model Innovation (BMI). The frequency and depth of these shifts can be conceptualized through the lens of Business Model Dynamics (BMD), which emphasizes how often and to what extent business model components are modified over time in response to changing technologies, markets, or regulatory environments (Khodaei & Ortt, 2019).

This chapter lays the theoretical foundation for analysing how digitization drives business model transformation in high-tech renewable energy firms. It introduces the core business model components-value creation, value delivery, and value capture-and defines the main change mechanisms (BMA, BME, BMI) as they relate to the evolving energy context. In doing so, it provides the conceptual tools required to understand and interpret the business model changes observed in both the literature and empirical interviews.

2.1 Key Business Model Concepts

To understand how digital technologies drive strategic change in renewable energy firms, it is essential to begin with a clear conceptualization of the business model and its components. A business model provides the structural logic through which a firm creates, delivers, and captures value. However, this structure is not static((Teece, 2010). As technologies evolve and market conditions shift, business models must also change, sometimes through small adaptations, sometimes through deeper structural transformations. To capture this range of changes, this study distinguishes between Business Model Adaptation (BMA), Business Model Evolution (BME), and Business Model Innovation (BMI). Together, these concepts describe how firms respond to digital transformation with varying degrees of intensity and strategic intent. Underlying these distinctions is the broader construct of Business Model Dynamics (BMD), which captures the frequency and extent of such changes over time (Khodaei & Ortt, 2019; Foss & Saebi, 2018).

This section introduces these key concepts in detail, beginning with the foundational components of business models-value creation, delivery, and capture-before defining each type of business model change and clarifying how they differ in scope and impact.

2.1.1 Business Model Components: Value Creation, Delivery, and Capture

Business models describe the logic of how organizations create, deliver, and capture value (Teece, 2010; Osterwalder & Pigneur, 2010). These three core components-value creation, value delivery, and value capture-form the foundation for understanding strategic business activities and are widely adopted in both academic and managerial discourse (Zott et al.,2011; Foss & Saebi, 2017).

Value creation refers to the processes, activities, and resources that enable a firm to develop offerings that fulfill customer needs. This includes tangible and intangible inputs such as technology, expertise, partnerships, and organizational capabilities. It reflects the firm's capacity to combine and orchestrate resources to generate meaningful customer outcomes (Lepak, Smith, & Taylor, 2007; Teece, 2010).

Value delivery encompasses the mechanisms through which a firm transfers its value proposition to customers. This involves the selection and configuration of channels, customer relationships, and infrastructure needed to deliver products or services effectively and reliably. Effective value delivery systems are critical for ensuring accessibility, usability, and satisfaction among end users (Osterwalder & Pigneur, 2010; Richardson, 2008).

Value capture pertains to how a firm monetizes the value it creates and delivers. It involves the revenue models, cost structures, and pricing strategies through which the firm sustains itself and generates profit. Capturing value requires not only effective pricing and payment mechanisms but also strategic control over key assets and relationships (Chesbrough, 2010; Massa, Tucci, & Afuah, 2017).

Together, these components constitute a firm's business model logic, enabling systematic analysis of how companies operate and compete. While they are often discussed separately, their effectiveness depends on internal coherence and alignment with the firm's strategic goals and external market conditions (Zott et al., 2011; Foss & Saebi, 2017).

2.1.2 Business Model Adaptation (BMA)

Business Model Adaptation (BMA) refers to targeted, non-disruptive changes that firms make to align their existing business model with evolving external conditions such as market volatility, shifting customer expectations, or new regulations. Saebi et al. (2017) define BMA as "the process by which management actively aligns the firm's business model to a changing environment," highlighting its strategic, yet non-radical nature. The emphasis is on preserving the overall business logic while making localized or tactical adjustments to one or more components.

These adaptations are often reactive, triggered by immediate threats or opportunities, yet can transition toward proactive value creation by enhancing environmental alignment (Guckenbiehl & Corral De Zubielqui, 2022). BMA is commonly linked to survival-oriented behaviors in uncertain environments (Balboni & Bortoluzzi, 2015). It allows firms to remain relevant by absorbing shocks through incremental adjustment, often guided by real-time feedback, trial-and-error learning, or reactive decision-making (Sosna et al., 2010). This learning-driven adaptation can involve upgrades to digital tools, changes in partnerships, or tweaks to pricing, but typically does not entail a systemic overhaul.

In this view, BMA functions as a first-order response , a way for firms to remain operationally viable while deferring more extensive transformation. It is an expression of strategic flexibility, enabling businesses to course-correct without destabilizing internal coherence.

2.1.3 Business Model Evolution (BME)

Business Model Evolution (BME) refers to the systematic and progressive refinement of a firm's business model over time. It involves interconnected changes across multiple business model components-such as value creation, delivery, and capture-while maintaining the underlying logic of how the firm operates. Unlike BMA, which may address isolated problems reactively, BME is often more strategic and internally driven, reflecting a firm's capability to adapt in a coherent and forward-looking manner (Saebi, 2014).

Central to BME is the idea of dynamic consistency(Demil & Lecocq, 2010): as one component changes, others are adapted in tandem to preserve overall alignment. For instance, when a firm integrates digital twins into its system design (value creation), this may lead to changes in delivery channels (e.g., self-service simulations) and pricing models (e.g., subscription-based offerings). These cross-component shifts are neither abrupt nor revolutionary, but cumulative and interdependent, reflecting an evolving business logic over time.

BME is often shaped by internal learning processes, such as long-term experimentation, capability development, and reflection, rather than one-off responses to external shocks. Khodaei and Ortt (2019) emphasize that evolution involves reconfiguring the business model as a system, integrating new technologies and capabilities while maintaining operational stability.

This approach is particularly suited to regulated or infrastructure-heavy sectors, such as renewable energy, where abrupt transformations are risky or impractical. In such contexts, BME enables firms to integrate digital technologies into their business gradually, improving efficiency, scalability, and responsiveness without triggering disruption.

In sum, BME reflects a deeper and more holistic shift than BMA, unfolding as an internally consistent and strategically coordinated evolution of the firm's business model in response to sustained change.

2.1.4 Business Model Innovation (BMI)

Business Model Innovation (BMI) refers to the intentional and strategic reconfiguration of how a firm creates, delivers, and captures value, often enabled or accelerated by external triggers such as technological advancement, market shifts, or policy change. In contrast to Business

Model Evolution (BME), which entails incremental adaptations, BMI involves deeper structural transformations that may challenge the firm's existing business logic or operational model (Amit & Zott, 2012; Foss & Saebi, 2017).

Such innovation can take multiple forms, including the development of entirely new value propositions, the introduction of novel delivery architectures (e.g., digital platforms or ecosystems), or rethinking revenue models (e.g., from product ownership to outcome-based pricing). Often, these shifts go beyond improving existing structures, they represent a redefinition of what the firm does and how it competes (Zott & Amit, 2013; Teece, 2018).

In many cases, BMI is enabled by digital technologies. Tools such as artificial intelligence (AI), the Internet of Things (IoT), and blockchain provide new capabilities for data-driven personalization, automation, decentralization, and service delivery. These technologies allow firms not only to optimize operations but also to explore new ways of engaging customers and generating revenue. As such, digitalization is often seen not just as a catalyst for operational upgrades but as a key driver of new business models (Foss & Saebi, 2017; Chesbrough, 2010).

Unlike adaptation, BMI typically involves deliberate managerial action, organizational learning, and experimentation (Sosna et al., 2010; Foss & Saebi, 2017). It may emerge through innovation labs, pilot projects, or collaboration with external partners. The process often challenges existing mental models, incentive systems, and resource allocation logics within the firm.

In the context of this study, BMI represents one end of the business model transformation spectrum. It reflects cases where digital technologies lead not just to component-level refinement but to systemic change, altering how firms define value, configure relationships, and organize their commercial logic (Geissdoerfer et al., 2018). Identifying such cases allows this research to differentiate between digitization as a means of optimization versus digitization as a catalyst for strategic renewal.

2.1.5 Business Model Dynamics (BMD)

As firms operate in rapidly changing environments shaped by digitalization, decarbonization, and decentralization, the need to continuously adjust their business models becomes an ongoing strategic imperative. This ongoing and iterative nature of change is captured by the concept of Business Model Dynamics (BMD), which refers to the patterns, frequency, and interdependence of changes across business model components over time (Khodaei & Ortt, 2019; Peñarroya-Farell & Miralles, 2021).

While concepts like Business Model Adaptation (BMA), Business Model Evolution (BME), and Business Model Innovation (BMI) describe different types or levels of change, BMD emphasizes the temporal and interconnected character of these transformations. It recognizes that business models are not static configurations but are continuously adjusted, recombined, or restructured in response to technological developments, market feedback, and organizational learning. As Peñarroya-Farell and Miralles (2021) note, BMD focuses on "how companies change and develop their business models to achieve sustained value creation through time."

Moreover, BMD encompasses varying strategic intensities of change (Peñarroya-Farell & Miralles, 2021). It includes incremental adaptations (BMA), cumulative refinements (BME), and disruptive reconfigurations (BMI), each representing different expressions of how business models evolve in response to internal and external stimuli. These modes of change can occur sequentially, interactively, or in combination, depending on the firm's context and maturity.

For instance, what begins as a small operational upgrade, such as automating a forecasting tool, can gradually alter value delivery mechanisms or pricing models, eventually leading to broader innovation in the firm's value logic. BMD helps to contextualize such multi-stage trajectories by examining how individual component changes interact and accumulate over time (Peñarroya-Farell & Miralles).

In this thesis, Business Model Dynamics (BMD) is not used as a direct coding category or analytical framework. Instead, it serves as a background perspective that helps interpret the changes observed across business models as part of a broader, ongoing process. This perspective supports the understanding that business model change in high-tech renewable energy firms is not always discrete or linear, but can unfold in reactive, evolutionary, or innovative ways depending on the context and depth of digital integration.

By acknowledging BMD, this study highlights that digitization does not lead to uniform or static outcomes. Instead, it opens space for diverse pathways of business model change, where firms may combine or transition between BMA, BME, and BMI over time.

These definitions were carefully selected and adapted to ensure conceptual clarity and analytical consistency across both the literature review and interview data. A more detailed explanation of the definitional approach is provided as a footnote in Appendix Table 1.

2.1.6 Working Definitions Used in This Study

To analyse how digital technologies influence business models in high-tech renewable energy firms, this study draws on four key concepts from the business model change literature: Business Model Adaptation (BMA), Business Model Evolution (BME), Business Model Innovation (BMI), and Business Model Dynamics (BMD). Although these terms are sometimes used interchangeably in academic discourse, they capture distinct types and degrees of business model change. The working definitions used in this thesis are synthesized from academic literature and conceptually grounded through a cross-paper comparison (see Appendix A - Tables A.1–A.4).

- *Business Model Adaptation (BMA)* refers to short-term, reactive adjustments in specific business model components in response to external disruptions (e.g., regulation, customer shifts, crises). These changes are typically incremental, localized, and tactical focused on maintaining operational continuity without altering the firm's core value logic or structure.
- *Business Model Evolution (BME)* refers to the gradual and coordinated refinement of business model components over time, such as delivery mechanisms, internal processes, or partner configurations, driven by accumulated learning or long-term shifts in technology and market context. While maintaining the firm's core value logic, BME enables improved alignment, internal consistency, and responsiveness across the business model.
- *Business Model Innovation (BMI)* refers to deliberate and transformational changes in the underlying logic of how a firm creates, delivers, and captures value. Often enabled

by digital technologies such as AI, IoT, or blockchain, BMI introduces novel value propositions, platform or service based delivery models, and alternative monetization mechanisms, requiring strategic repositioning and system-wide reconfiguration of business model elements.

Table 2. Summary of Business Model Change Concepts (under the broader lens of Business Model Dynamics) Used in this Thesis

Concept	Definition	Key Characteristics	Examples of Triggers/Drivers Found in our Research
Business Model Adaptation (BMA)	Short-term, reactive adjustments to specific BM components	Incremental, localized, tactical; no change in core value logic	External shocks, regulation, crises, customer shifts
Business Model Evolution (BME)	Gradual and coordinated refinement of BM components over time	Internally driven; cumulative learning; improved alignment without altering value logic	Learning-by-doing, technology shifts, market maturation
Business Model Innovation (BMI)	Transformational change in how value is created, delivered, and captured	New value logic; reconfigured delivery and monetization; system-wide impact	Strategic repositioning, digital technologies (AI, IoT, blockchain)

***NOTE: Definitions of BMA, BME, BMI, and BMD(below) used in this study are based on prior literature but were carefully adapted to ensure conceptual clarity and empirical usability. We selected only those framings that could be consistently distinguished based on scope and depth of change, while avoiding overlapping or ambiguous formulations that could blur the lines between categories.*

- *Business Model Dynamics (BMD)* refers to the ongoing, iterative nature of business model change, shaped by cycles of experimentation, learning, and adjustment. Rather than representing a single shift, BMD highlights how firms may transition across different types of change (e.g., adaptation, evolution, innovation) over time. In this thesis, BMD is not applied as a direct analytical category but serves as a background concept to interpret whether observed transformations reflect isolated adjustments or form part of a longer-term reconfiguration process.

2.2 Digital Technologies and Business Model Change in Renewable Energy

Digital technologies are increasingly central to the transformation of firms across industries, including the renewable energy sector. While initially deployed to support operational tasks such as automation, remote monitoring, and diagnostics, these technologies have evolved into strategic enablers that redefine how firms create, deliver, and capture value (Ahmad et al., 2021; Hu et al., 2022). Tools like artificial intelligence (AI), the Internet of Things (IoT), blockchain, cloud computing, and digital twins are now embedded across infrastructure, customer interfaces, and service architectures, supporting new ways to manage assets, interact with stakeholders, and offer flexible energy solutions (Adnan et al., 2024; Plewnia, 2019).

Recent studies highlight that digital transformation (DT) is not merely a matter of technological deployment but a broader strategic and organizational process. It reconfigures internal competencies, customer interfaces, and operational logics, often leading to a redefinition of the business model itself (Malewska et al., 2024). In the renewable energy context, DT is increasingly regarded as a prerequisite for adapting to decentralized, data-driven energy systems that demand agility, responsiveness, and cross-sector integration (Malewska et al., 2024).

These developments have far-reaching implications. Firms are not only digitizing internal processes but also redesigning value propositions, delivery mechanisms, and revenue models to align with new digital and sustainability logics (Gitelman & Kozhevnikov, 2023; Liu et al., 2022). Examples include the rise of prosumer engagement models, digital finance integration, and real-time, usage-based service delivery. While many academic studies describe these shifts in terms of platforms, service models, or customer experience, they implicitly point toward significant business model reconfigurations, especially in how value is co-created and monetized.

This section synthesizes recent literature to explore how key digital technologies are deployed within the renewable energy sector and what types of organizational and market changes they are enabling. The aim is not to apply a fixed business model typology, but to remain grounded in empirical findings while identifying broader implications for business model transformation. These patterns lay the foundation for later chapters, where this thesis systematically examines the types and depths of business model change across multiple case firms.

2.2.1 Foundational Technologies and Operational Transformation

A foundational set of digital technologies, particularly artificial intelligence (AI), the Internet of Things (IoT), digital twins, and cloud computing, are transforming operational capabilities across the renewable energy sector. These technologies, originally introduced for monitoring, control, and fault detection, now underpin more strategic shifts in how firms manage distributed infrastructure, reduce uncertainty, and design flexible service models (Ahmad et al., 2021; Hu et al., 2022; Adnan et al., 2024).

AI and IoT are especially prominent in enabling intelligent automation. AI-driven models are used for energy forecasting, anomaly detection, and generation scheduling, often trained on real-time weather, consumption, and asset performance data to optimize system operations and reduce forecasting errors (Ahmad et al., 2021; Adnan et al., 2024; Franki et al., 2023). In parallel, IoT devices deployed across generation and storage assets provide granular, real-time data that supports predictive maintenance, consumption analytics, and demand-side flexibility (Hu et al., 2022; Singh et al., 2021).

Cloud computing serves as the integration layer that connects these distributed assets and enables service delivery. It allows firms to remotely manage energy systems, host digital dashboards for users, and deploy AI-based analytics at scale (Adnan et al., 2024). Cloud platforms also support the orchestration of distributed energy resources (DERs) through centralized or hybrid control models, especially relevant for firms managing geographically dispersed infrastructure.

Digital twins extend these capabilities by creating real-time, virtual replicas of physical assets or systems. These models integrate sensor data and simulate performance under varying conditions to predict failures, optimize maintenance schedules, and improve decision-making (D'Amore et al., 2022). Their use reduces operational risk and enables condition-based maintenance without physical inspection, particularly valuable in complex, remote, or off-grid installations.

Together, these technologies also form the operational backbone of Virtual Power Plants (VPPs), which represent an emerging digital coordination model. By integrating AI, cloud systems, and control algorithms, VPPs enable real-time orchestration of decentralized assets like solar, wind, and battery storage. Bähr and Fliaster (2023) describe how such platforms support smart forecasting, load balancing, and remote command execution, allowing firms to manage distributed infrastructure as cohesive, intelligent systems.

Evidence from German energy startups further illustrates this trend. Singh et al. (2021) report that early-stage firms are actively combining AI, IoT, and cloud to develop flexible, data-centric business models. These include applications such as customer-specific energy optimization, predictive analytics, and real-time pricing mechanisms, extending the role of digital technologies beyond technical efficiency into commercial strategy.

These shifts suggest that digitalization is not confined to back-end automation but is also shaping the architecture of energy services and firm-level decision-making. As emphasized by Malewska et al. (2024), Singh et al. (2021), and Franki et al. (2023), these technologies support more responsive, automated, and customer-aligned operations, paving the way for new business configurations that differ substantially from traditional utility models.

2.2.2 Digital Platforms and Business Model Innovation

The rise of digital platforms marks a significant shift in how renewable energy firms structure their services, coordinate with stakeholders, and innovate their business models. Digital Technology Platforms (DTPs), as defined by Bartczak (2021), are modular digital infrastructures that facilitate interaction, data exchange, and service delivery across diverse actors in the energy ecosystem. Unlike traditional software tools, DTPs enable continuous adaptation, integration of new services, and expansion of user-facing capabilities, forming the backbone of many digitally enabled energy businesses (Bartczak & Łobejko, 2022; Malewska et al., 2024).

These platforms support a wide range of functions, from remote asset monitoring and user interface customization to algorithmic sales automation and embedded finance. Their modular and open architectures allow energy firms to personalize offerings, integrate third-party solutions, and evolve with changing market demands (Bartczak & Łobejko, 2022). For example, a single platform may offer real-time consumption insights, appliance control, predictive maintenance services, and payment management, within a unified digital environment.

Beyond technical enablement, DTPs act as strategic vehicles for business model innovation. Malewska et al. (2024) argue that platform-based structures allow firms to shift from infrastructure ownership toward orchestrating interactions and services. These models support prosumer participation, co-creation, and personalized engagement, facilitating transitions from commodity sales to experience- and data-driven service offerings. This trend reflects a broader movement toward customer-centric and decentralized logic in the renewable energy sector.

Digital platforms are also key to the emergence of Everything-as-a-Service (XaaS) models, especially among startups. Singh et al. (2021) find that German energy startups are increasingly adopting multi-sided platforms that support peer-to-peer trading, e-mobility integration, and subscription-based services. These platforms combine hardware and software layers to deliver tailored solutions while enabling flexible pricing, real-time responsiveness, and new value capture mechanisms. However, Singh et al. (2021) also note that these models often coexist with traditional B2B/B2C setups, resulting in hybrid business logic that is still evolving.

Notably, digital platforms allow firms to operate without directly owning or controlling all resources. Value is created through orchestration, by facilitating exchanges between prosumers, analytics providers, financial partners, and other ecosystem actors (Bartczak, 2021). As these platforms scale, they benefit from network effects and data aggregation, reinforcing their centrality in the value chain.

Although many reviewed studies do not use formal business model frameworks, their descriptions imply fundamental changes in value creation, delivery, and capture. DTPs allow firms to reposition themselves, not just as energy suppliers but as digital service providers capable of evolving rapidly with user needs and system complexity. This modular and extensible approach provides the flexibility needed to operate in increasingly dynamic, prosumer-driven energy landscapes.

2.2.3 Virtual Power Plants as Platforms for Digital Energy Orchestration

Virtual Power Plants (VPPs) are one of the most prominent applications of digital transformation in the renewable energy sector. By integrating decentralized energy resources, such as rooftop solar, wind turbines, battery storage, and demand-side assets, VPPs enable firms to orchestrate distributed capacity as a single, intelligent system. These systems rely heavily on AI-driven forecasting, cloud computing, IoT-based telemetry, and remote control software to dynamically balance load, optimize generation, and enhance grid stability (Bähr & Fliaster, 2023; Franki et al., 2023).

Functioning as advanced digital coordination platforms, VPPs consolidate foundational technologies into scalable architectures that support system-level optimization. Bähr and Fliaster (2023) describe how energy firms use VPP platforms to execute real-time command sequences, automate dispatch strategies, and interface with both wholesale markets and local grid operators. In doing so, VPPs move beyond operational tools, they serve as strategic assets that reshape how firms coordinate value delivery across geographic and organizational boundaries.

Importantly, the strategic role that VPPs play depends on how firms conceptualize their purpose. Bähr and Fliaster (2023) identify two distinct framings: a single-focused frame, where VPPs are viewed primarily as efficiency-enhancing tools that improve profitability through smart automation and load balancing; and a twofold frame, which positions VPPs as enablers of both economic and societal goals. In the twofold frame, firms also use VPPs to facilitate prosumer participation, support regional energy resilience, and advance sustainability objectives. This distinction is critical, as it influences whether digital platforms like VPPs are deployed merely to optimize existing operations or whether they catalyse deeper forms of business model transformation by embedding new forms of stakeholder engagement and co-creation.

Startups are increasingly adopting VPP-like strategies through lightweight, cloud-native platforms that enable them to aggregate and control distributed energy assets without the need for heavy infrastructure. Singh et al. (2021) observe that early-stage firms are layering digital technologies, such as machine learning, IoT sensors, and cloud-based applications, on top of solar, battery, or smart device networks to enable features like real-time pricing, automated energy control, and peer-to-peer (P2P) trading. While these setups may not resemble full-scale VPPs operated by utilities, they replicate many of the same functions on a smaller, modular scale.

Whether implemented by incumbents or startups, VPPs illustrate how digital infrastructure and platform logic can converge to deliver real-time energy services. They transform firms from static asset operators into dynamic aggregators, integrating flexibility, responsiveness, and personalization into their value proposition. As such, VPPs reflect not only technological advancement but also a strategic reconfiguration of business model components, particularly in value delivery and coordination mechanisms.

2.2.4 Blockchain, Smart Contracts, and Peer-to-Peer Energy Models

Blockchain and smart contract technologies are increasingly explored in the renewable energy sector as tools to support secure, transparent, and decentralized coordination. Unlike traditional centralized systems, blockchain operates on a distributed ledger, allowing verified transactions between parties without intermediaries. This makes it particularly well-suited for enabling peer-to-peer (P2P) energy trading, decentralized ownership models, and automated service execution (Mika & Goudz, 2021; Augello et al., 2022).

In several studies, blockchain is positioned as the foundational layer for energy platforms that connect producers and consumers directly. These systems often incorporate smart contracts, self-executing agreements encoded on the blockchain, which automate tasks such as payment processing, energy usage verification, and contract enforcement (Plewnia, 2019; Mika & Goudz, 2021). The result is a reduction in administrative overhead, faster transaction cycles, and more transparent service delivery.

Blockchain also enables key functions that support sustainability and regulatory objectives. Augello et al. (2022) emphasize its role in energy traceability and origin verification, particularly for green energy, allowing consumers to confirm the source of their electricity and engage in ethical consumption. Meanwhile, Mika and Goudz (2021) show how blockchain facilitates the creation of local energy markets, where surplus power generated by rooftop solar panels can be securely shared or sold among community members via micro-transactions.

Empirical evidence from energy startups reinforces blockchain's role in operational innovation. Singh et al. (2021) report that German energy startups are integrating blockchain into their service layers to streamline billing, automate P2P trading, and enable seamless supplier switching. These startups often combine blockchain with AI and IoT to support real-time tracking, forecasting, and transaction execution, resulting in digitally native service models that are transparent, user-controlled, and data-driven.

These developments are not only operational but also strategic in nature. Blockchain-enabled energy models shift control toward the edge of the network, empowering prosumers, communities, and cooperatives to become active participants in energy exchange. This decentralization challenges the traditional utility-customer hierarchy and introduces new business model logics based on transparency, automation, and distributed trust (Plewnia, 2019).

Furthermore, blockchain facilitates innovative revenue mechanisms. Instead of relying solely on fixed tariffs or subscription plans, firms can adopt micro-payment structures, usage-based billing, or tokenized incentive systems. While many studies do not explicitly frame these changes as business model transformations, the underlying technological affordances suggest a significant rethinking of how energy services are configured, delivered, and monetized.

2.2.5 Grid-Side Digitalization and Infrastructure Platforms

Digitalization is not limited to customer-facing platforms or decentralized systems, it also plays a crucial role in the modernization of core energy infrastructure. Distribution system operators (DSOs), in particular, are investing in digital technologies to enhance grid observability, flexibility, and responsiveness. Leiva Vilaplana et al. (2025) highlight that alongside physical grid reinforcement, DSOs are adopting smart meters, substation automation, and AI-based monitoring systems to collect real-time data, simulate intervention strategies, and automate dispatch decisions. These capabilities are vital for managing the increased complexity introduced by distributed energy resources (DERs) and intermittent renewable generation.

Such digital upgrades enable DSOs to detect grid congestion risks, balance local supply and demand, and improve fault diagnostics, all of which are difficult to achieve with legacy systems. In doing so, digital infrastructure transforms traditional grid operations into adaptive, data-driven environments capable of supporting prosumer activity, bidirectional energy flows, and localized energy services (Leiva Vilaplana et al., 2025).

Liu et al. (2022) further emphasize that grid-side digitalization underpins a broader shift in energy system architecture, from centralized utility models to intelligent, decentralized ecosystems. In these emerging configurations, power, information, and control circulate across a distributed network of users, devices, and service providers. Technologies such as cloud computing, digital twins, and smart control algorithms enable operators to manage thousands of connected nodes in real time, optimize load balancing, and integrate flexibility as a core operational function.

These digital capabilities are not merely technical enablers, they also open up new strategic and commercial opportunities. For example, Liu et al. (2022) argue that digital grid platforms can offer value-added services such as grid-responsiveness, automated flexibility provisioning, and reliability guarantees. Firms can monetize not only the energy itself but also their capacity to manage coordination complexity and deliver system stability.

As a result, digital infrastructure becomes a foundation for new forms of value creation and delivery. While many of these developments are led by DSOs or technology providers rather than energy retailers, the implications for business models are significant. The ability to embed intelligence into grid operations enables firms to develop new service offerings, improve integration with customer-facing platforms, and reposition themselves within emerging energy ecosystems.

2.2.6 Emerging Markets and PAYG Innovation

Emerging markets have become important testbeds for digitally enabled business model innovation, especially in contexts where traditional grid infrastructure is limited or unreliable. One of the most prominent examples is the Pay-As-You-Go (PAYG) model, which blends digital metering, mobile payments, and cloud-based analytics to deliver decentralized renewable energy as a service. Rasagam and Zhu (2018) describe how PAYG systems are particularly effective in rural areas of Sub-Saharan Africa, where they enable low-income households to access solar power through affordable, usage-based payments.

In a typical PAYG setup, customers purchase modular solar kits embedded with IoT-enabled devices that allow firms to monitor usage, remotely activate or deactivate systems, and offer upgrade options. These systems are managed via cloud platforms and often integrated with GSM connectivity to support real-time diagnostics and service control (Rasagam & Zhu, 2018). Payments are made through mobile money systems, allowing customers to pay in small, flexible increments that match their income patterns, substantially lowering the financial barriers to energy access.

What makes the PAYG model transformative is how it integrates energy supply, digital finance, and customer analytics into a single, service-based offering. Firms collect behavioural and usage data to assess creditworthiness, personalize energy plans, and cross-sell complementary services such as appliance bundles, insurance, or microloans. Over time, some PAYG providers have evolved from energy suppliers into multi-service digital platforms, offering energy access alongside financial and lifestyle services within the same ecosystem (Rasagam & Zhu, 2018).

Although many studies describe these developments from a technology or access perspective, the business model implications are significant. PAYG shifts the firm's role from one-time asset provider to ongoing service orchestrator. It redefines revenue models around recurring payments, reduces reliance on traditional infrastructure, and introduces flexible ownership and consumption options for users.

This model also introduces new dynamics in value co-creation. Customers gain more control over their energy experience while contributing data and feedback that inform product evolution. At the same time, firms benefit from embedded user relationships, real-time operational control, and scalable service delivery. These digitally mediated dynamics suggest a move toward platform-based, participatory business models that are both contextually adapted and commercially sustainable.

2.2.7 Conclusion: Digitalization and the Reconfiguration of Business Models

Taken together, the reviewed literature demonstrates that digital technologies are not merely technical enhancements but act as catalysts for profound structural change in the renewable energy sector. They enable new forms of coordination, automate decision-making, and support real-time responsiveness, reshaping how firms interact with infrastructure, stakeholders, and markets. Across contexts and configurations, a clear pattern emerges: digitalization drives a shift from centralized utility models toward decentralized, platform-based ecosystems. In this new architecture, value is co-created with prosumers, services are orchestrated through modular digital platforms, and revenue models evolve to reflect data-driven, usage-based, and participatory logics. While the literature varies in how explicitly it engages with business model frameworks, it consistently points toward reconfigurations in value creation, delivery, and capture. These patterns provide the conceptual and empirical grounding for the next chapter, where we systematically examine how different firms' business model change through digital integration.

2.3 Literature Gap

Although digital technologies such as AI, IoT, blockchain, and cloud computing are widely discussed in the renewable energy literature, particularly in terms of optimization, automation, and system performance (Ahmad et al., 2021; Adnan et al., 2024), many studies still overlook how these technologies reshape firm-level business models (Franki et al., 2023), especially in relation to value creation, delivery, and capture. For example, while Yu et al. (2024) present a rich dataset on digital transformation in Chinese energy firms using keyword-based metrics covering a wide range of technologies, they do not examine how these technologies affect specific business model components. Similarly, Wang et al. (2025) analyze the impact of digital transformation on productivity but do not detail how individual digital tools influence the structure or evolution of the business model. Even when business model innovation (BMI) is addressed, it is typically approached in fragmented terms. Ancillai et al. (2023) observe that most studies focus on isolated components, failing to explore interdependencies between them or how changes triggered by digital technologies cascade across business model architecture.

A second limitation concerns the lack of empirical use of business model change typologies. While distinctions between business model adaptation (BMA), evolution (BME), and innovation (BMI) are well-developed conceptually (Foss & Saebi, 2017; Khodaei & Ortt, 2019), they are rarely applied to examine how different firms respond to digitalization in practice. Most research treats digital transformation as a general enabler of innovation, without differentiating between incremental adjustments and more systemic shifts. Both Wang et al. (2025) and Yu et al. (2024) treat digital transformation as a macro-level driver of performance improvement, but they do not categorize or interpret changes in terms of BMA, BME, or BMI. As a result, the mechanisms through which firms shift their value logic or organizational configuration remain unspecified.

There is also limited research on smaller and digitally embedded renewable energy firms. Much of the literature focuses on large utilities, donor-backed pilots, or national-scale platforms (Malewska et al., 2024; Pakulska & Poniatowska-Jaksch, 2022), while firms operating in more modular, product-based, or decentralized settings receive comparatively little attention. This includes high-tech SMEs that design hardware-software bundles, deploy cloud-based simulations, or offer mobile-enabled energy services. Studies that do explore such firms, such as Singh et al. (2021), Rasagam and Zhu (2018), and Mika and Goudz (2021), often treat them as case-specific innovations rather than as entry points into broader discussions of business model change. As a result, the literature provides limited insight into how digitally enabled business models are developed or sustained in more flexible, bottom-up, or resource-constrained contexts.

Another gap concerns how digital infrastructures are linked to strategic decision-making. While technologies like smart meters, IoT platforms, AI systems, and blockchain are increasingly studied for their technical potential (Liu et al., 2022; Leiva Vilaplana et al., 2025; K.N. et al., 2024), there is little investigation into how firms translate these digital technologies into market-facing innovations, new service architectures, or changes in value capture logic. The business-level implications of adopting these tools remain underexplored, especially in cases where digital systems enable firms to reposition themselves or expand their roles within the energy ecosystem.

This thesis addresses these gaps by examining how high-tech renewable energy firms use digital technologies to influence value creation, delivery, and capture. Both interview data and a systematic literature review were independently coded using the Gioia methodology, covering business model components and change types (BMA, BME, BMI). The two datasets were then compared to identify convergences and differences in how digitalization drives business model change. Rather than providing a generalized classification, the study interprets these patterns to offer a grounded, component-level understanding of digitalization's role in business model transformation within a specific but underexplored segment of the renewable energy sector.

2.4 Conceptual Model

To guide the empirical investigation of how digital technologies influence business model change in the renewable energy sector, this study presents a conceptual framework that synthesizes key theoretical concepts outlined in Section 2.1.6. The model does not aim to establish deterministic relationships between digital tools and business model outcomes. Instead, it adopts an exploratory, multi-pathway approach that accommodates variation in firm responses, reflecting the dynamic and context-dependent nature of strategic change.

At its core, the framework is built upon the three foundational business model components- value creation, value delivery, and value capture (Osterwalder & Pigneur, 2010; Teece, 2010). These components represent the building blocks through which firms configure resources, activities, and relationships to generate and sustain competitive advantage. The study focuses specifically on how these components are reshaped when firms adopt or deploy digital technologies.

Digital technologies such as Artificial Intelligence (AI), Internet of Things (IoT), Blockchain, Cloud platforms, and Digital Twins serve as key enablers of transformation. These technologies can enhance forecasting, automate processes, decentralize transactions, personalize user experience, or enable platform-based service delivery. However, their impact on business models is not uniform: the same technology may trigger incremental change in one firm, while prompting strategic reinvention in another.

To account for this variation, the framework distinguishes between three types of business model change, previously discussed:

- **Business Model Adaptation (BMA**) refers to short-term, reactive modifications to specific components of the business model. These changes often emerge in response to external disruptions (e.g., regulatory shifts, crises, customer demands) and are typically localized and tactical, such as introducing a new pricing mechanism or digital interface, while preserving the firm's overall value logic.

- **Business Model Evolution (BME)** refers to the gradual refinement of business model components over time, driven by accumulated learning or progressive technological integration. Unlike BMA, which is often short-term and reactive, BME reflects a longer-term process aimed at improving internal consistency, efficiency, or strategic responsiveness. These changes may affect one or more components, such as delivery mechanisms, partnerships, or monetization models, but do not disrupt the firm's overarching value logic.
- **Business Model Innovation (BMI)** entails a deliberate and often radical reconfiguration of how value is created, delivered, and captured. It may involve shifting from product-based to service- or platform-based models, introducing novel value propositions, or establishing entirely new monetization mechanisms. BMI typically requires strategic repositioning and deep internal realignment of business model components.

These categories are not mutually exclusive. In practice, firms may transition across them, evolving from adaptation to innovation, as digital maturity increases and capabilities deepen.

To reflect the iterative and layered nature of business model change, this study draws on the concept of Business Model Dynamics (BMD) as a background perspective. Rather than treating business model transformation as a one-time event, BMD emphasizes that firms often engage in multiple, overlapping adjustments in response to technological, market, or organizational shifts. While this thesis does not conduct a formal temporal or longitudinal analysis, the interviews include reflections on how firms' approaches have evolved over time, such as how their digital strategy or value proposition has developed since inception. By incorporating BMD in an interpretive way, the study aims to capture the cumulative and non-linear character of business model change in digitally active high-tech renewable energy firms.

Figure 1 below visually represents this conceptual model.

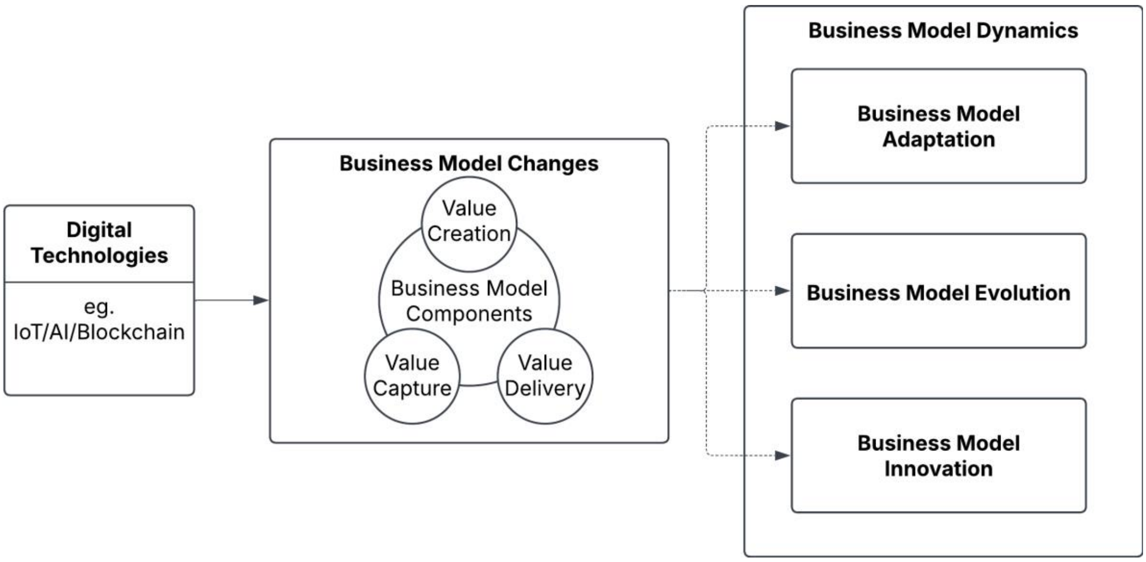

Figure 1. Conceptual Model

3 Methodology

3.1 Research Design

To build a foundational understanding of the topic, define key theoretical constructs and identify literature gaps, the study initially employed a narrative literature review (Baumeister & Leary, 1997). This exploratory phase helped surface core concepts, such as digital technologies, business model components, and the distinction between Business Model Adaption (BMA), Business Model Evolution (BME) and Business Model Innovation (BMI) under the broader lens of Business Model Dynamics (BMD) - which helped the refinement of the research focus.

To ensure a holistic and grounded understanding, the study integrates two distinct but complementary data sources: a systematic literature review (SLR) and a multiple-case interview study. The SLR enables a structured synthesis of prior academic work on digital technologies and business model innovation in the renewable energy sector, following transparent selection and screening procedures (Tranfield, Denyer, & Smart, 2003).

The empirical phase of the research involves semi-structured interviews with key stakeholders from five Dutch firms engaged in renewable energy technologies and services. Firms were selected based on their relevance to the renewable energy sector and indications that they were engaging with digital technologies in meaningful ways. While clear evidence of business model change was not always available in advance, the sampling strategy focused on firms that appeared likely to offer insights into how digitalization may influence value creation, delivery, or capture. The aim was not to test predefined hypotheses, but to explore a range of real-world experiences that could inform an empirically grounded understanding of how digitalization contributes to either business model adaptation (BMA), business model evolution (BME) or business model innovation (BMI) across different firm contexts.

The research design follows an iterative logic that moves back and forth between empirical data and theoretical concepts to develop novel insights. This abductive process allows the researcher to refine or reframe existing theoretical constructs based on patterns or themes that emerge from the data (Timmermans & Tavory, 2012). Such an approach is especially useful in domains characterized by rapid innovation and conceptual ambiguity, where digital technologies such as AI, IoT, and blockchain are not merely operational tools but actively reshape the core value propositions, delivery mechanisms, and revenue structures of business models.

The design is tightly aligned with the Gioia methodology (Gioia, Corley, & Hamilton, 2013), which offers a robust framework for inductively developing concepts while maintaining methodological rigor. This method involves systematic coding, categorization, and visual representation of data in a way that preserves informant-centric terms and meanings, before abstracting them into higher-order theoretical themes. As such, the Gioia methodology aligns well with abductive reasoning, enabling the development of theory while preserving the depth of participants' experiences and the contextual meanings they associate with digital transformation and business model change.

By combining a qualitative approach focused on understanding participants' perspectives, an abductive logic of inquiry, and two complementary data sources, literature and interviews, this study is positioned to generate nuanced insights into how digital technologies shape business model innovation and evolution in the renewable energy sector. The chosen methodology ensures that emergent patterns and contradictions are not overlooked, but rather used as entry points for deeper theorization. This is particularly important in the energy domain, where digitalization is not just a technological shift but a potential enabler of new socio-technical configurations and market logics.

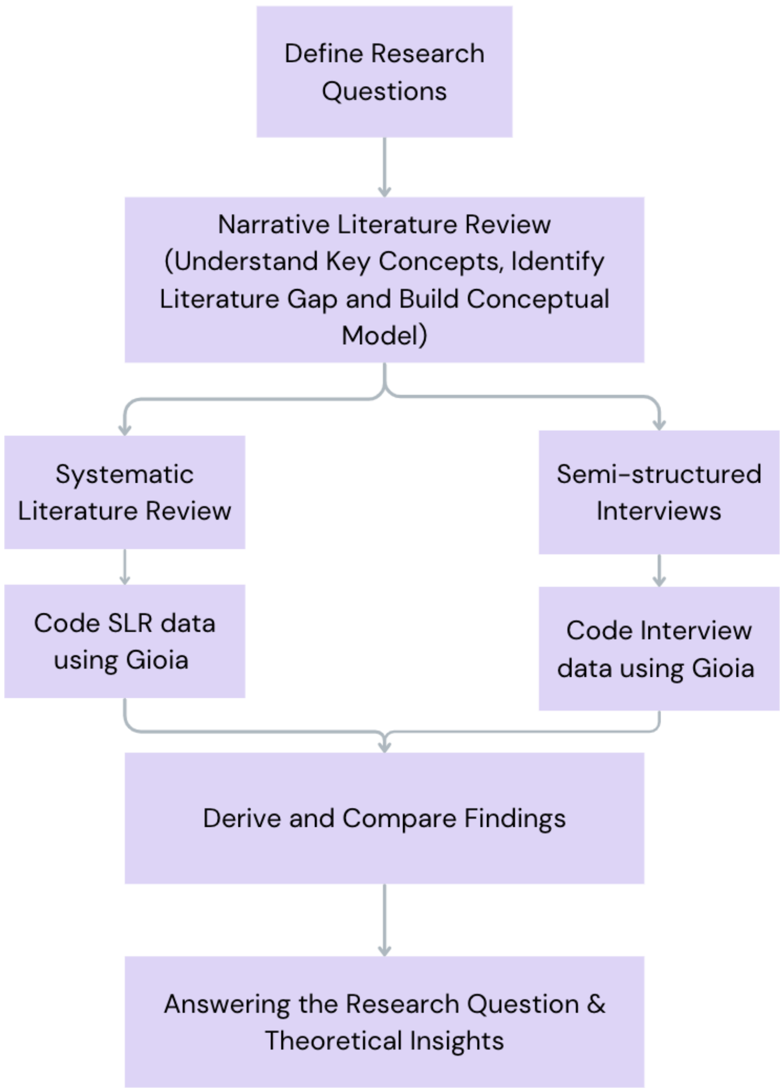

Figure 2.Overview of Research Design and Analytical Workflow

3.2 Case and Participation Selection

This study adopts a multiple-case design to examine how digital technologies influence business model transformation in the renewable energy sector in the Netherlands. The firms were selected for their theoretical relevance to the research objectives. This approach aligns with the study's aim to understand how diverse firms interpret and engage with digitization-related business model changes in their specific organizational contexts.

Five firms were selected using criterion-based purposive sampling (Patton, 2002). Selection was guided by preliminary indicators such as digital focus in offerings or processes, strategic or innovation-oriented positioning, and sectoral relevance. The firms span various niches within the renewable energy ecosystem, offering analytic breadth across business models and organizational types:

- Firm A – A venture capital firm focused solely on renewable energy startups
- Firm B – A circular solar solutions provider
- Firm C – A smart energy hardware and data company
- Firm D – An energy simulation SaaS platform
- Firm E – A modular solar systems provider for emerging markets

Table 3. Participant Roles and Firm Description

Code	Firm Description	Role Interviewed	Company Age
Firm A	Venture capital firm investing in renewable energy startups	Associate	5 years
Firm B	Circular and sustainable solar solutions provider	Technical Lead	5 years
Firm C	Smart energy hardware and digital services firm	Director	5 years
Firm D	Energy simulation SaaS firm	CEO / Co-founder	1.5 years
Firm E	Modular solar systems firm targeting emerging markets	Commercial Director	12 years

These organizations vary in age (1.5 to 12 years), and each participant held a strategic or technical leadership role (e.g., associate, technical lead, director, co-founder, commercial director), ensuring access to firsthand insights into both digital activities and business model development. In some cases, participants provided access to internal materials to supplement the interview data.

3.3 Data Collection

3.3.1 Systematic Literature Review (SLR)

To provide a robust theoretical foundation for the empirical phase of this study, a systematic literature review (SLR) was carried out to examine how digital technologies are influencing business model transformation in the renewable energy sector. The review followed the PRISMA 2020 guidelines (Page et al., 2021), which emphasize methodological transparency, replicability, and structured reporting in literature-based research.

The SLR aimed to synthesize emerging patterns and knowledge gaps in this evolving domain. Given its wide coverage of peer-reviewed journals in business, management, and energy research, Scopus was selected as the primary database. It is frequently used in systematic reviews across these domains and is recognized for its reliability in identifying high-quality academic literature (Endres & Weibler, 2017; Dada, 2018;). The approach was informed by systematic review principles outlined by Tranfield et al. (2003), adapted for use in interpretive and theory-building research.

1. Planning the Review

The search strategy reflected three intersecting domains central to this thesis:

- Sectoral scope: renewable or sustainable energy
- Theoretical scope: business model innovation, evolution, or dynamics
- Technological scope: digital technologies or digitization

The search string applied to Scopus was:
("Digital technologies" OR "Digitization") AND ("Renewable Energy" OR "Sustainable Energy") AND ("Business model innovation" OR "Business model evolution" OR "Business model adaptation" OR "Business model dynamic")

The following inclusion criteria were used:

- Language: English
- Source type: Peer-reviewed journal articles
- Publication period: 2015 to 2025

2. Conducting the Review

The initial search post filters yielded 150 articles. These were filtered through a multi-step screening process:

- A title and abstract screening reduced the pool to 61 articles, based on relevance to the research scope.
- A full-text review further excluded retracted articles, inaccessible content, or papers that did not address the research topic. This resulted in a final set of 29 papers.

The entire screening process followed the PRISMA 2020 framework and is illustrated in the PRISMA flow diagram (Figure 3).

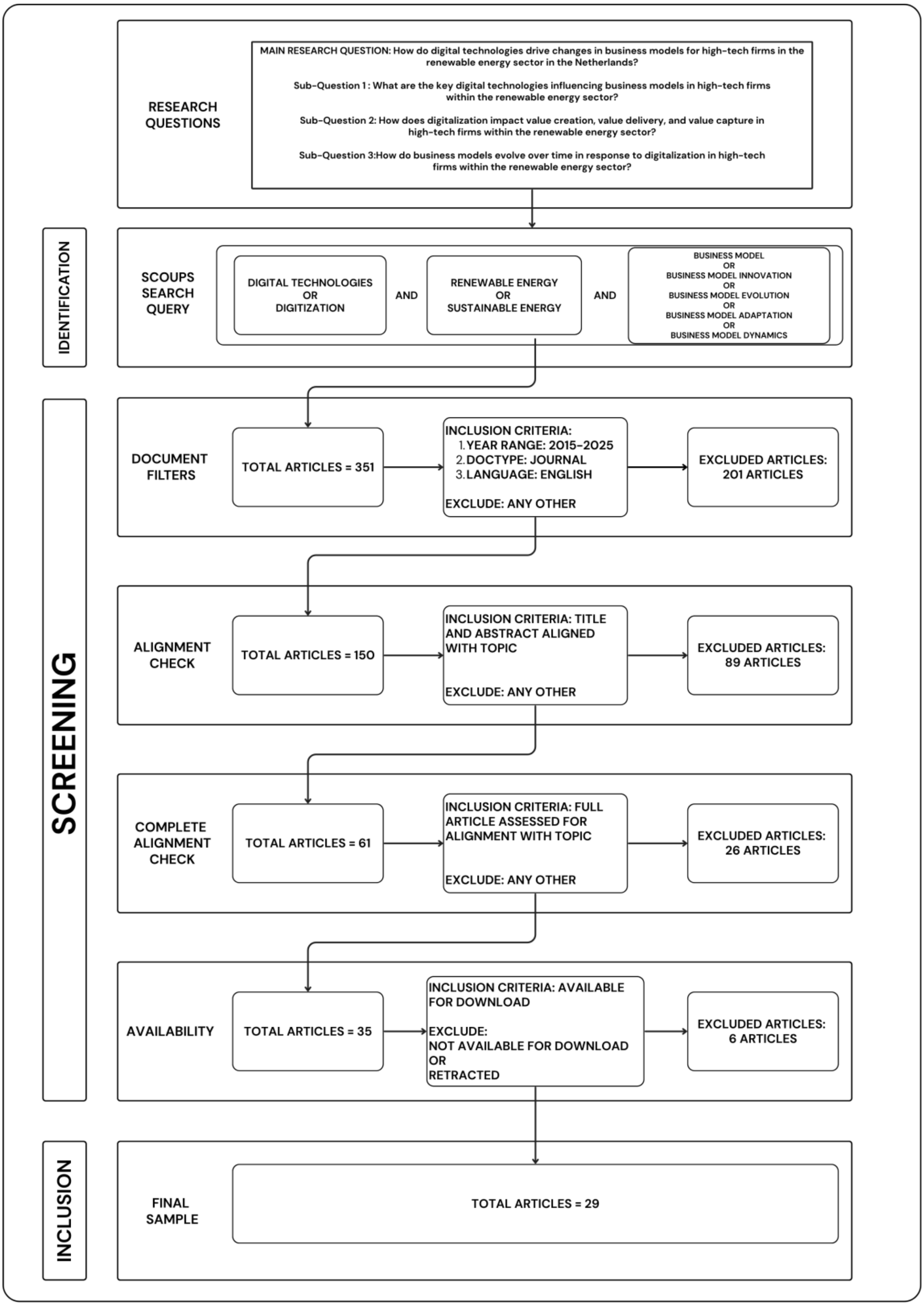

Figure 3. SLR Prisma Flow Diagram

3. Analysing the Results

Each of the 29 articles was analysed using the Gioia methodology (Gioia, Corley, & Hamilton, 2013). First-order concepts were extracted directly from the literature to reflect empirical observations. These concepts were then grouped into second-order themes through interpretive coding, capturing deeper theoretical patterns across the studies. Finally, the second-order themes were synthesized into aggregate dimensions, corresponding to the core business model elements: value creation, value delivery, value capture, or overarching change categories like BMA, BME or BMI.

The SLR was designed not only to summarize the existing body of research, but also to identify conceptual structures that would complement the interview findings and inform the coding architecture used in the qualitative phase. This parallel integration of literature and empirical data enhanced analytical rigor and ensured consistency in how digital technologies and business model transformation were conceptualized across both data streams.

3.3.2 Interview Data Collection and Protocol

To capture detailed, context-rich insights into how firms perceive and experience business model change through digital technologies, the study conducted semi-structured interviews with one participant from each of the five selected firms. This method was chosen for its flexibility and ability to elicit nuanced, real-world narratives while maintaining comparability across cases (Kallio et al., 2016).

Participants were identified and invited using purposive outreach, primarily through LinkedIn and the researcher’s personal network. Personalized invitations briefly explained the study’s purpose and sought consent for participation.

Each interview lasted approximately 30 to 45 minutes and was conducted via Microsoft Teams, providing a secure and flexible environment for data collection. With participant consent, all interviews were recorded and transcribed for analysis. A semi-structured interview guide was used to ensure thematic consistency while allowing for open-ended discussion. Key areas explored included the firm’s use of digital technologies (e.g., AI, IoT, cloud-based tools) , the observed changes in value creation, delivery, or capture and overall business model change effects.

Participants were briefed before each session regarding the study’s scope, data handling protocols, and their rights. A digital informed consent form, covering voluntary participation, anonymity, data protection, and withdrawal rights, was shared and signed prior to the interview. Participants could ask clarifying questions, and a summary of key insights was shared with them post-interview for validation.

All data were handled according to TU Delft’s Human Research Ethics Committee (HREC) protocols. A data management plan was approved by the HREC on 22 April 2025, and all materials are securely stored on TU Delft’s OneDrive, accessible only to the researcher. These records will be permanently deleted after the study concludes to ensure full confidentiality and compliance with ethical standards.

3.4 Data Analysis via Gioia Methodology

To guide the analysis of interview data in a structured and theory-building manner, this study applied the Gioia methodology. This approach supports the development of new conceptual frameworks grounded in participant experiences and empirical evidence, making it particularly well-suited for exploratory research on under-theorized topics (Gioia et al., 2013) such as digitization-driven business model change in the renewable energy sector.

The coding process followed the Gioia model's three-tiered structure. First, excerpts from interview transcripts were organized into first-order concepts, these were phrased as closely as possible to participants' expressions, though mostly paraphrased to reflect the underlying meaning of their responses. Each concept represented a distinct insight about digital technology use, and its perceived impact on business practices.

In the second stage, related first-order concepts were grouped into second-order themes. These themes reflected more abstract interpretations that offered preliminary explanations about the mechanisms through which digital technologies interacted with organizational practices. At this stage, the analysis focused on how these digital tools appeared to shape or support changes in business activities, particularly across dimensions such as value creation, delivery, and capture.

Finally, the second-order themes were distilled into broader aggregate dimensions, corresponding to the three core business model components: Value Creation, Value Delivery, and Value Capture (Teece, 2010). This approach aligns with the study's aim to trace the influence of digitization on specific elements of business models. In addition to this structure, a second coding framework was applied to interpret the nature of business model change itself. While the first Gioia coding tree mapped interview insights onto the business model components of value creation, delivery, and capture, the second tree classified the type of change observed, distinguishing between Business Model Adaptation (BMA), Business Model Evolution (BME), and Business Model Innovation (BMI), as defined in Section 2.1. This dual coding approach enabled a richer analysis by linking specific digital technology influences not only to the structural dimensions of business models but also to the depth and trajectory of change within each firm.

The same Gioia-inspired coding structure was also applied to the Systematic Literature Review (SLR) findings to maintain analytical coherence across data sources. To maintain analytical clarity, the SLR and the interview dataset were coded separately, each with its own Gioia table and coding structure. While the SLR coding helped identify theoretical building blocks and existing perspectives, the interview-based analysis enabled inductive theorizing grounded in contemporary, real-world accounts. This separation ensured that each data source contributed uniquely to the development of findings, while still supporting broader triangulation across the study.

Throughout the process, data were coded using structured spreadsheets and iterative memo-writing to refine interpretations. The Gioia approach allowed for transparency in how abstract themes were developed from empirical input, making it well-suited to the abductive and interpretive orientation of this research. The method has been widely adopted in qualitative management research for its rigor in concept development and clarity in linking raw data to emerging theory (Gioia et al., 2013; Gehman et al., 2018).

3.5 Research Quality and Ethics

To ensure the credibility and academic rigor of this study, careful attention was paid to both research quality criteria and ethical safeguards throughout the design and implementation phases. In qualitative research, the validity of findings does not rest on statistical generalizability but on the depth, transparency, and trustworthiness of the research process (Shenton, 2004).

Credibility was enhanced through several strategies. First, the use of semi-structured interviews allowed participants to reflect freely on their experiences, leading to rich and contextually grounded data. Triangulation across two independent data sources, the Systematic Literature Review (SLR) and interviews, further strengthened the study by enabling convergence and comparison of insights from theoretical and empirical perspectives.

Additionally, response validation was employed by sharing key interview summaries with participants to confirm the accuracy of interpretations. This form of member checking supports the internal validity of qualitative studies by minimizing researcher bias in representing participant viewpoints (Birt et al., 2016).

Transparency was also maintained through detailed documentation of each step in the research process, from sampling and data collection to coding and analysis. Gioia methodology was used not only to structure the data but to show clearly how first-order concepts evolved into theoretical themes, preserving a clear link between participant input and emergent theory.

The study fully adheres to ethical research practices as defined by TU Delft's Human Research Ethics Committee (HREC). Prior to data collection, each participant was provided with a digital informed consent form, which clearly outlined the purpose of the study, the voluntary nature of participation, data confidentiality, and rights of withdrawal. Participants were invited to raise questions, and interviews were only conducted after explicit consent was received.

To ensure privacy and data security, all interviews were conducted using Microsoft Teams, and recordings and transcripts were securely stored on TU Delft's OneDrive, accessible only to the researcher. These will be permanently deleted upon completion of the project. The consent form and data management plan were reviewed and approved by TU Delft's HREC on 22 April 2025. The interview process and the use of human data were handled in accordance with ethical guidelines for research involving human participants. A summary of each participant's key insights was shared after the interview to confirm accuracy and reduce the risk of misrepresentation. All names and organizational identifiers have been anonymized using firm codes (Firm A to E) to protect identities.

4 Results

4.1 Overview of Data and Coding Structure

We present the empirical results of the study based on two key sources of data: (1) semi-structured interviews conducted with experts and practitioners in the renewable energy sector, and (2) a systematic literature review (SLR) of academic publications focused on digital technologies and business model transformation. Both data sources were analysed using the Gioia methodology, which emphasizes inductive category building through a grounded and systematic coding process. The following subsections outline the composition of each dataset and the approach used to extract and organize key concepts, themes, and dimensions that underpin the subsequent findings.

4.1.1 Overview of Data and Coding Structure

This study conducted five semi-structured interviews between May and June 2025 to explore how digital technologies drive changes in business models within the renewable energy sector. Each interview lasted approximately 30 to 45 minutes and was conducted online via secure video conferencing platforms. All sessions were recorded (with participant consent), transcribed verbatim, and analysed using the Gioia methodology, which supports inductive theory-building based on grounded qualitative insights.

To preserve confidentiality and encourage openness, firm and participant identities were anonymized.

This diversity in firm types and roles enriches the comparative insights drawn in later. The interviews were coded in multiple cycles following the Gioia methodology. First-order concepts were extracted using the language and terminology of the participants. These were then grouped into more abstract second-order themes that reflected interpretive patterns. The coding structure was aligned with the three primary business model components-value creation, value delivery, and value capture-to enable structured cross-case comparison.

4.1.2 SLR Dataset Summary

To complement the interview-based analysis, a structured Systematic Literature Review (SLR) was conducted to examine how digital technologies influence business model change in the renewable energy sector. The review covered a total of 29 peer-reviewed academic papers selected through a multi-phase screening and inclusion process, focusing on research related to digital technologies and business model transformation in renewable energy contexts.

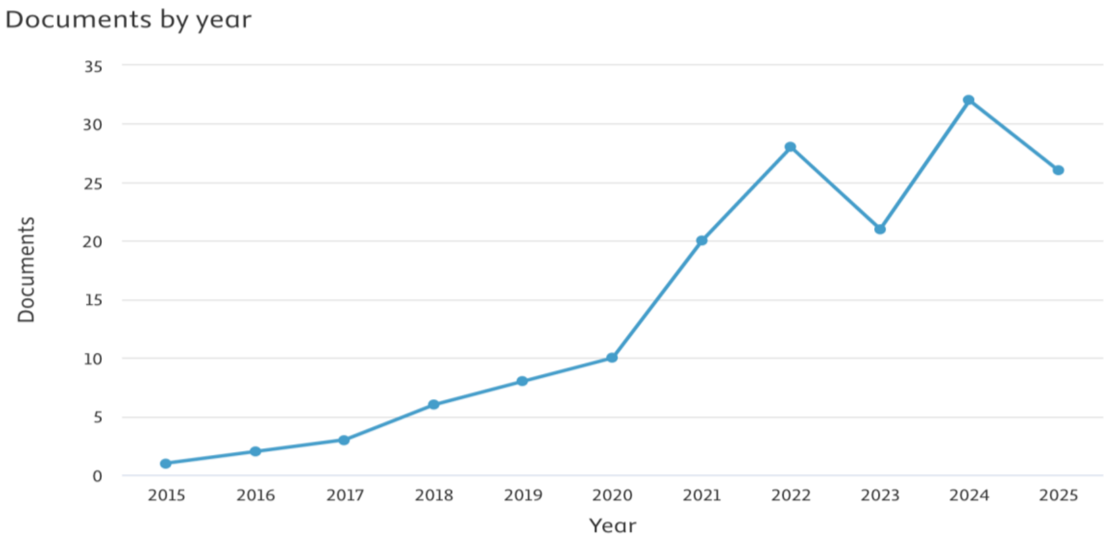

Figure 4. Distribution of SLR Papers by Year of Publication

Figure 4 illustrates the distribution of these papers by year of publication. The temporal clustering shows that most contributions emerged between 2021 and 2025, reflecting a recent surge in academic interest. This concentration also confirms that the digital transformation of business models in renewable energy is an emerging field of inquiry that has gained momentum only in the past few years.

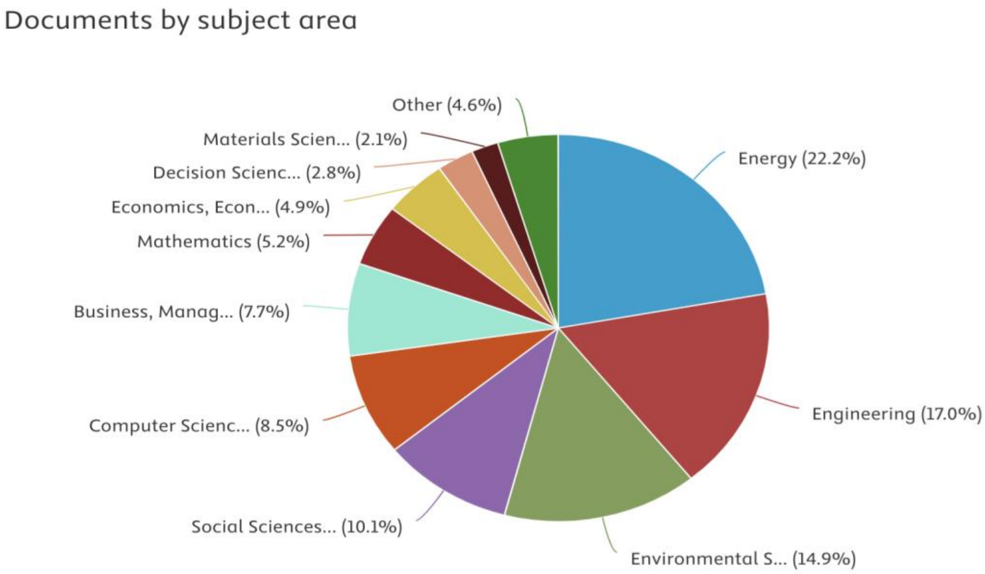

Figure 5. SLR Papers by Subject Area (Scopus Classification)

Figure 5 shows the subject area classification of these papers based on Scopus indexing. The dataset spans multiple disciplines, including energy systems, environmental science, computer science, and sustainability. However, contributions from the business and management domain remain relatively limited. This disciplinary gap reinforces the importance of the present study, which seeks to bridge the technical and strategic dimensions of digitalization by analysing how digital technologies reshape business model components and transformation trajectories.

Each paper was analysed using the Gioia methodology, allowing for the inductive development of first-order categories, second-order themes, and aggregate dimensions. The analysis focused on how digital technologies were linked to transformations in business model components-value creation, value delivery, and value capture-as well as their role in different types of business model change, including adaptation (BMA), evolution (BME), and innovation (BMI). The resulting coding structures are presented in sections ahead and organized using the same two Gioia trees employed for the interview data.

4.2 Findings from Interview Analysis Using the Gioia Methodology

4.2.1. Digital Technologies' Influence on Business Model Components

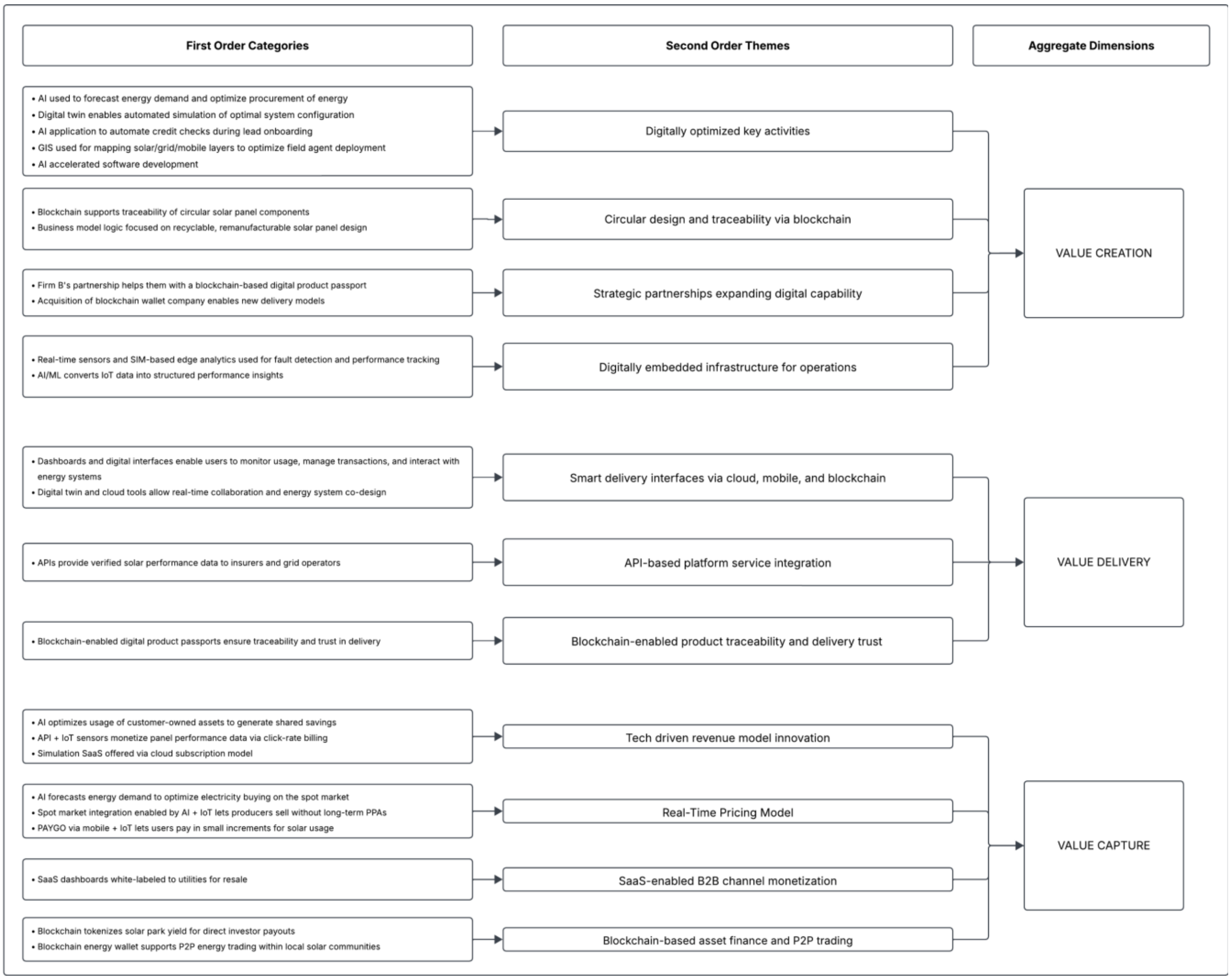

Figure 6. Interview Gioia Coding Structure of Business Model Components

Figure 6. illustrates the finalized data structure. It connects the insights from interviews to the thematic patterns that emerged, offering a comprehensive view of how AI, IoT, blockchain, digital twins, and cloud-based systems reshape core business model elements. Each of the following subsections analyses one aggregate dimension. Interpretations are supported by direct quotes to ground the insights in participant experiences.

Value Creation

The analysis revealed that digital technologies play a foundational role in shaping how renewable energy firms create value. Across the five firms, four major themes emerged: optimization of key activities, embedded technical infrastructure, circular design principles, and strategic partnerships enabling new capabilities.

Digitally Optimized Key Activities

Several firms leveraged digital technologies to enhance the efficiency, accuracy, and responsiveness of their core activities , from system planning and forecasting to onboarding and software development.

Firm A, a venture capital investor in energy startups, described how AI is applied by portfolio companies to support energy forecasting and cost optimization:

> *"They use AI to understand the production processes… and then they optimise the procurement of electricity to that time in the spot market."* (Firm A)

Firm D used digital twin simulations to optimize system configuration, reducing manual effort and improving precision:

> *"The system design process has become far more efficient… now we can simulate dozens of variations in real-time."* (Firm D)

Firm E is developing AI-based automation in lead onboarding, where AI listens to customer conversations and tailors follow-up questions for credit checks:

> *"We are now developing a way on how to use AI… where AI can listen into the conversations and give some questions depending on the answers…"* (Firm E)

In the same firm, GIS technology is employed to optimize sales agent deployment by layering solar coverage, grid proximity, and mobile network access:

> *"They are able to analyze a certain area… see what is the layer of grids… make a map of where the agent should go to sell, so as to increase the chance of your sales."* (Firm E)

Firm D also noted how AI accelerated their internal development process, significantly reducing time-to-market:

> *"What we built in one year… would have taken 3–4 years before AI."* (Firm D)

These cases collectively illustrate how digital tools , including AI, GIS, and digital twin technologies , enable digitally optimized key activities, streamlining operations and expanding delivery potential.

Digitally Embedded Infrastructure for Operations

Firm C emphasized the role of sensors, SIM cards, and AI in enabling real-time fault detection, performance monitoring, and insight generation from deployed solar systems:

"There's also sensors with SIM cards that track system performance locally... we can see faults, generate alerts, and even correct some of them." (Firm C)

They also described how AI/ML models convert raw IoT data into structured insights that can be monetized or used for decision-making:

"Our business model is to packetize that data into different ML and AI data sets and insights." (Firm C)

These technologies form the core technical infrastructure of operations, embedding intelligence into assets and creating a dynamic resource base for system-wide optimization.

Circular Design and Traceability via Blockchain

Firm B demonstrated a sustainability-first value logic, grounded in the circular design of solar panels intended for remanufacturing and recyclability:

"That was the idea , to create a very sustainable solar panel… it's meant to be circular." (Firm B)

To support this vision, blockchain is used to trace the origin, material composition, and life-cycle data of solar panels through a digital product passport, in collaboration with Circularise:

"There is a digital product passport from one of our stakeholders… Circularise." (Firm B)

These efforts represent a shift toward circular design as a core value proposition, supported by digital technologies that embed transparency and traceability into the product lifecycle.

Strategic Partnerships Expanding Digital Capability

Several firms relied on strategic partnerships to extend their digital capabilities. Firm B's collaboration with Circularise, for instance, allowed them to adopt blockchain-based traceability without building the tech in-house.

Firm C also described how acquiring a company in Italy with a blockchain-enabled energy wallet helped them accelerate the delivery of peer-to-peer energy solutions:

"We've acquired a company in Italy with a blockchain energy wallet… Now we can support peer-to-peer energy transactions inside solar communities." (Firm C)

These cases underscore how partnerships serve as enablers of digital infrastructure, expanding what firms can offer without internal development overhead. These digital enhancements to value creation predominantly support incremental and evolutionary business model changes. Firms leverage technologies such as AI, IoT, and blockchain to optimize their core processes and embed transparency, thereby establishing a foundation that enables broader transformational shifts explored further in Section 4.2.2.

Value Delivery

Digital technologies have reshaped how renewable energy firms deliver value to customers, partners, and other stakeholders. Across the studied firms, three main changes emerged in how services are presented, integrated, and trusted: through user interfaces, platform-level integrations, and blockchain-supported verification tools.

Smart Delivery Interfaces via Cloud, Mobile, and Blockchain

A major trend observed was the use of smart, technology-enabled delivery interfaces. Firms A, C, and E each employ digital platforms , ranging from cloud dashboards to mobile applications and blockchain wallets , to help users and partners monitor energy use, manage services, or conduct transactions in real time.

Firm A described how one of their portfolio companies enables property managers to view live consumption through a digital dashboard:

> *"They use the dashboard for the property manager to show them what's happened and what is happening under live consumption."* (Firm A)

Firm E similarly employs a mobile platform for both end users and B2B partners to manage prepaid energy services and recharges:

> *"We use pay-as-you-go solar systems with mobile payments… [Customers] get real-time insights and control."* (Firm E)

Firm C integrates a secure digital wallet and Unity dashboard into its platform to allow solar asset users to monitor performance and engage in energy transactions:

> *"We've acquired a company in Italy with a blockchain energy wallet… Now we can support peer-to-peer energy transactions inside solar communities."* (Firm C)

In addition, Firm D offers a cloud-based energy simulation tool that allows co-designing of energy systems:

> *"It allows portability over different devices… sharing work much easier… estimating solar panels automatically."* (Firm D)

Together, these cases demonstrate how cloud, mobile, and blockchain technologies are forming a smart delivery layer, allowing customers and users to interact seamlessly with energy systems.

Platform-Level Integration via APIs

Firm C also enables real-time performance validation through platform-based service integration using APIs. This allows grid operators, insurers, and third parties to plug into their ecosystem to access verified solar panel data:

> *"Through our API, insurers and grid operators can plug in to access verified panel performance."* (Firm C)

This highlights the importance of API-based integration as a delivery channel , not for end-users directly, but for institutional actors who require data to interact with and validate energy performance remotely.

Blockchain-Enabled Product Traceability and Delivery Trust

In both Firm B and Firm C, blockchain technology plays a key role in ensuring trust and transparency in the delivery process. Firm B has partnered with Circularise to create blockchain-based digital product passports that track components throughout the supply chain:

> *"There is a digital product passport from one of our stakeholders, also from the Netherlands , Circularise."*(Firm B)

Firm C similarly uses SIM-based blockchain integration at the panel manufacturing stage to embed traceability into the product itself:

> *"At the solar panel factory, we're able to use the SIM profile… blockchain ready to make a digital product passport of the solar panel."* (Firm C)

These examples show how blockchain is used not only for transactional purposes but also for delivery verification and traceability, especially in sustainability-conscious, high-trust environments.

The innovations observed in value delivery, through cloud platforms, dashboards, and digital twins, reflect a spectrum of business model evolution and adaptation. These advancements enhance customer engagement and operational responsiveness, corresponding to the business model change classifications discussed in detail later

Value Capture

Revenue Model

Digital technologies are significantly shaping revenue models across firms in the renewable energy sector. In this study, Firms A, C, and D provided illustrative examples of how AI, IoT, API integration, and SaaS platforms are creating new monetization pathways.

Firm A, a venture capital firm investing in renewable energy startups, highlighted multiple portfolio companies using AI to drive asset-based monetization strategies. One such firm uses AI to optimize client-owned energy assets and engage in shared savings:

> *"They use AI to understand production processes and optimize electricity usage. That optimization helps reduce energy costs for industrial clients, and the savings are monetized through a shared model between the client and the startup."* (Firm A)

Firm C leverages AI/ML, IoT sensors and APIs to transform raw operational data into sellable insights. Their model charges third parties such as insurers and grid operators based on data access volume:

> *"We discharge a click rate for the data… Our business model is to packetize that data into different ML and AI data sets and insights, and eventually sell clicks and access to API data streams."* (Firm C)

Firm D adopted a cloud-based SaaS approach by offering its energy simulation platform through a subscription model. This shift allowed them to scale service delivery while securing consistent revenue:

> *"We offer our simulator as a SaaS product now… it allows us to scale better and deliver value on a recurring basis."* (Firm D)

These cases collectively illustrate how AI, APIs, and SaaS platforms are enabling revenue model innovation in digital energy firms, transforming value capture from static product sales to dynamic service-based income streams.

Pricing Mechanism

Several firms are transitioning from fixed pricing to more responsive and flexible models, supported by AI, IoT, and mobile payment infrastructure.

Firm A shared an example from a startup in their portfolio that uses AI to dynamically manage industrial electricity procurement:

> *"They use AI to understand the production processes and when there's an uptick in energy use expected… then they optimize the procurement of electricity to that time in the spot market. Therefore they decrease the prices the industry player pays."* (Firm A)

Firm C enables solar park owners to participate directly in spot energy markets, bypassing traditional long-term PPAs. This strategy provides asset owners with greater yield potential:

> *"We offer a way that we can get better yield on the solar panel asset… by letting the people play the spot market instead of being forced into 12 years of industrial servitude with a low price PPA."* (Firm C)

Firm E implements a pay-as-you-go (PAYGO) model using mobile payments and IoT monitoring, enabling users to pay in small increments:

> *"We use pay-as-you-go solar systems with mobile payments to let people pay in small increments over time… It's key for affordability and access."* (Firm E)

These developments highlight how digital technologies like AI, IoT, and mobile platforms are enabling dynamic and flexible pricing strategies aligned with market conditions and user ability to pay.

B2B / Partner Channel

Firm A also observed B2B channel innovation among its portfolio companies through white-labeled SaaS solutions. One such startup licenses dashboards to utility clients and corporate resellers:

> *"It's a software product for most of the time utility or big corporate offering, oftentimes a white label to smaller resellers or customers."* (Firm A)

This use of SaaS infrastructure supports partner-driven revenue generation and platform-based scalability in energy software delivery.

Asset Monetization / Financial Model

Firm C stood out in its use of blockchain to create new financial and ownership structures within the solar energy ecosystem.

One initiative involves tokenizing the revenue streams of solar parks and distributing yields directly to token-holding investors:

> *"One of them would be real-world asset tokenization… A programmatic yield from that solar park can be paid out to the coupon holders. The coupon holders are token holders in this case."* (Firm C)

Another initiative involves enabling decentralized peer-to-peer trading within solar communities via a blockchain energy wallet:

> *"Energy can be transacted on the same network... through peer-to-peer trading... We've acquired a company in Italy with a blockchain energy wallet."* (Firm C)

These innovations represent a radical shift from conventional energy finance, demonstrating how blockchain is unlocking tokenized asset finance and decentralized transaction models for renewable energy firms.

The variety of digital monetization approaches, from traditional SaaS subscriptions to emerging tokenization models, demonstrates different levels of business model evolution and innovation. These patterns are further contextualized in the analysis of business model change types presented subsequently.

4.2.2 Digital Technologies Influencing Business Model Change

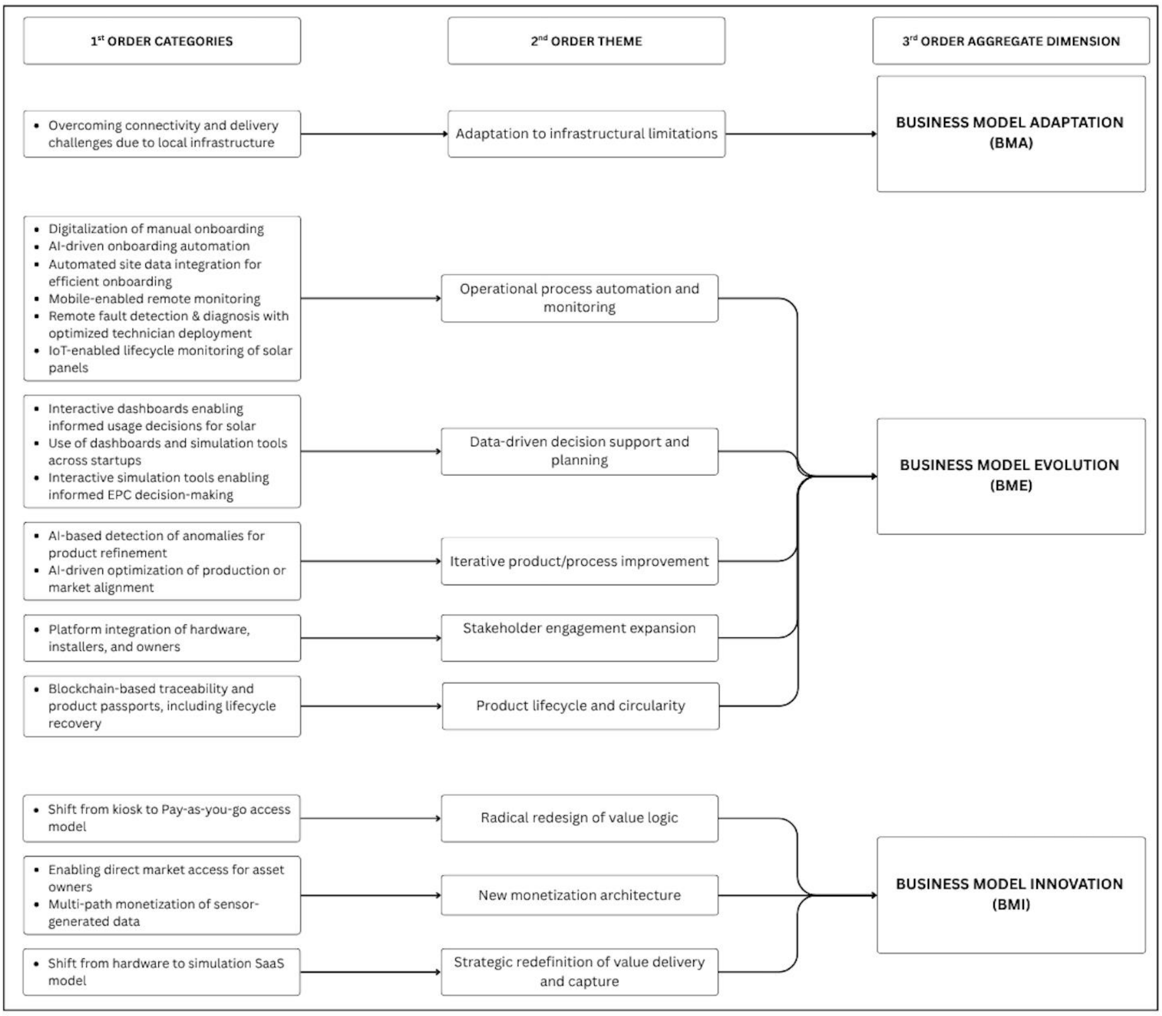

Figure 7. Interview Gioia Coding Structure of Business Model Change Types

This Figure 7 presents the Gioia coding derived from interview data, where the first-order categories represent raw interview concepts and actions, the second-order themes interpret mechanisms and patterns of business model change, and the third-order aggregate dimensions classify these changes into Business Model Adaptation (BMA), Evolution (BME), and Innovation (BMI). Each of the following subsections analyses one aggregate dimension. Interpretations are supported by direct quotes to ground the insights in participant experiences.

Business Model Adaptation (BMA)

Business Model Adaptation (BMA) refers to incremental, context-driven adjustments firms make to their existing business models to align with local environmental, infrastructural, or operational constraints. Unlike evolution or innovation, BMA involves fine-tuning existing components without fundamentally redefining value creation, delivery, or capture.

Within our dataset, BMA is primarily characterized by a single key theme:

Adaptation to infrastructural limitations

Firms operating in infrastructure-constrained environments frequently adapt their delivery mechanisms to accommodate infrastructural constraints. For example, Firm E described overcoming connectivity challenges by implementing local caching to enable system operation in offline modes, synchronizing data only when network access becomes available:

> *"In some regions, mobile networks are weak. We've had to adapt by building local caching so the system works offline and syncs later when it gets a signal." (Firm E)*

This example illustrates a targeted and context-specific modification that preserves core business logic while ensuring operational continuity under adverse conditions.

Such adaptations highlight the pragmatic and reactive nature of BMA, reflecting firms' efforts to maintain service delivery quality without undertaking broad structural or strategic changes. Building on these adaptive changes, firms also undertake evolutionary transformations that refine and expand their core business activities.

Business Model Evolution (BME)

Business Model Evolution (BME) encompasses incremental to substantial changes that refine or expand existing business model components. These changes improve efficiency, capabilities, or scope but do not fundamentally alter the underlying value creation, delivery, or capture logic.

Our analysis identified several key themes under BME, revealing how firms leverage digital technologies to enhance operational workflows, decision support, stakeholder engagement, and product lifecycle management.

Operational process automation and system monitoring

Firms employ digital tools to automate core processes and improve monitoring capabilities. For example, Firm E described the evolution of their onboarding system:

> *"Earlier we had local sales agents managing onboarding through manual forms… Now, we've integrated the credit scoring and onboarding into our app." (Firm E)*

They also reported innovations in remote system management:

> *"We also monitor the system remotely, so if there's a technical fault, we can send someone with the right equipment , no more trial-and-error field visits." (Firm E)*

Data-driven decision support and planning

Several firms enhance decision-making through dashboards and simulation tools. Firm D emphasized:

> *"The platform helps EPCs compare different design scenarios quickly… so instead of gut feeling, they now make data-driven investment decisions." (Firm D)*

Firm C integrates multiple data sources to provide comprehensive system views:

> *"It was important that we bring together the field hardware, the monitoring dashboards, the installer input, and the owner's asset view, all in one place." (Firm C)*

Data-driven iterative improvement of value creation

AI analytics enable continuous product refinement, as noted by Firm C:

> "*We try to really use AI in a very, very good way to understand what are the abnormalities, what is a trend… we will see a massive drop in battery capacity at what temperature… So really trying to analyze and then design our products accordingly." (Firm C)*

Structural expansion of stakeholder engagement channels

Some firms build integrated platforms connecting multiple stakeholders, facilitating collaboration and transparency, exemplified by Firm C's platform integration described above.

Traceable product identity for circular delivery

Firm B leverages blockchain to enhance traceability and lifecycle management:

> "*We're using blockchain through a partnership with Circularise to track material provenance and enable product passports. So each panel has a verifiable identity and history , from raw material to assembly to field use. We embed traceability from the start , so when a panel comes back after 10 or 15 years, we know exactly what it contains, where it came from, and whether parts are reusable or recyclable." (Firm B)*

These findings collectively illustrate how firms use digital technologies to incrementally refine and expand their business models, enhancing operational efficiency, decision-making capabilities, stakeholder collaboration, and product lifecycle management. While these changes stop short of fundamental reinvention, they represent significant steps toward more responsive and data-driven renewable energy business models.

Business Model Innovation (BMI)

Business Model Innovation (BMI) involves fundamental and often disruptive changes that redefine how firms create, deliver, and capture value. Unlike evolution or adaptation, BMI introduces new logics, revenue mechanisms, and market approaches that can reshape industries and competitive dynamics.

Our analysis uncovered several prominent themes under BMI, illustrating how firms in the renewable energy sector leverage digital tools to enact these radical transformations.

Radical redesign of value logic

Firm E exemplifies a fundamental shift in their access and delivery model. They moved away from a centralized kiosk system to a scalable pay-as-you-go system that has enabled significant growth:

> *"We started off with the concept… a centralized kiosk system… But we finally figured out… this is not scalable. And then we moved into this pay-as-you-go system… and that has massively scaled up." (Firm E)*

New monetization architecture

Firm C pioneers new monetization avenues by allowing asset owners direct participation in spot energy markets, redefining how value is captured:

> *"We offer a way that we can get better yield on the solar panel asset… by letting the people play the spot market instead." (Firm C)*

Additionally, they create a multi-path data economy leveraging sensor-generated information for various services:

> *"Our proprietary sensor generates high-fidelity field data , and we monetize it multiple times, from insurance analytics to programmable energy to investor dashboards. We don't just sell panels; we build a data economy around them." (Firm C)*

Strategic redefinition of value delivery and capture

Firm D transitioned from hardware deployment to a purely cloud-based simulation software platform, radically altering their business offering and revenue structure:

> *"It was mostly hardware-based in the beginning, yes. And that was very difficult to scale. And so, now it's completely cloud-based. We have a software tool that you can use without installing anything. You just log in and start simulating." (Firm D)*

These examples demonstrate how digital technologies enable profound reconfigurations of renewable energy business models. Through radical redesigns of access mechanisms, innovative monetization structures, and strategic pivots to new service platforms, firms are not only responding to market demands but actively shaping future industry landscapes.

This section as a whole presents a hierarchical analysis of business model change types as identified through the Gioia methodology. It shows how firms' use of digital technologies results in different degrees of transformation, classified as Business Model Adaptation, Evolution, or Innovation.

4.3 Findings from SLR Analysis Using the Gioia Methodology

4.3.1. Digital Technologies' Influence on Business Model Components

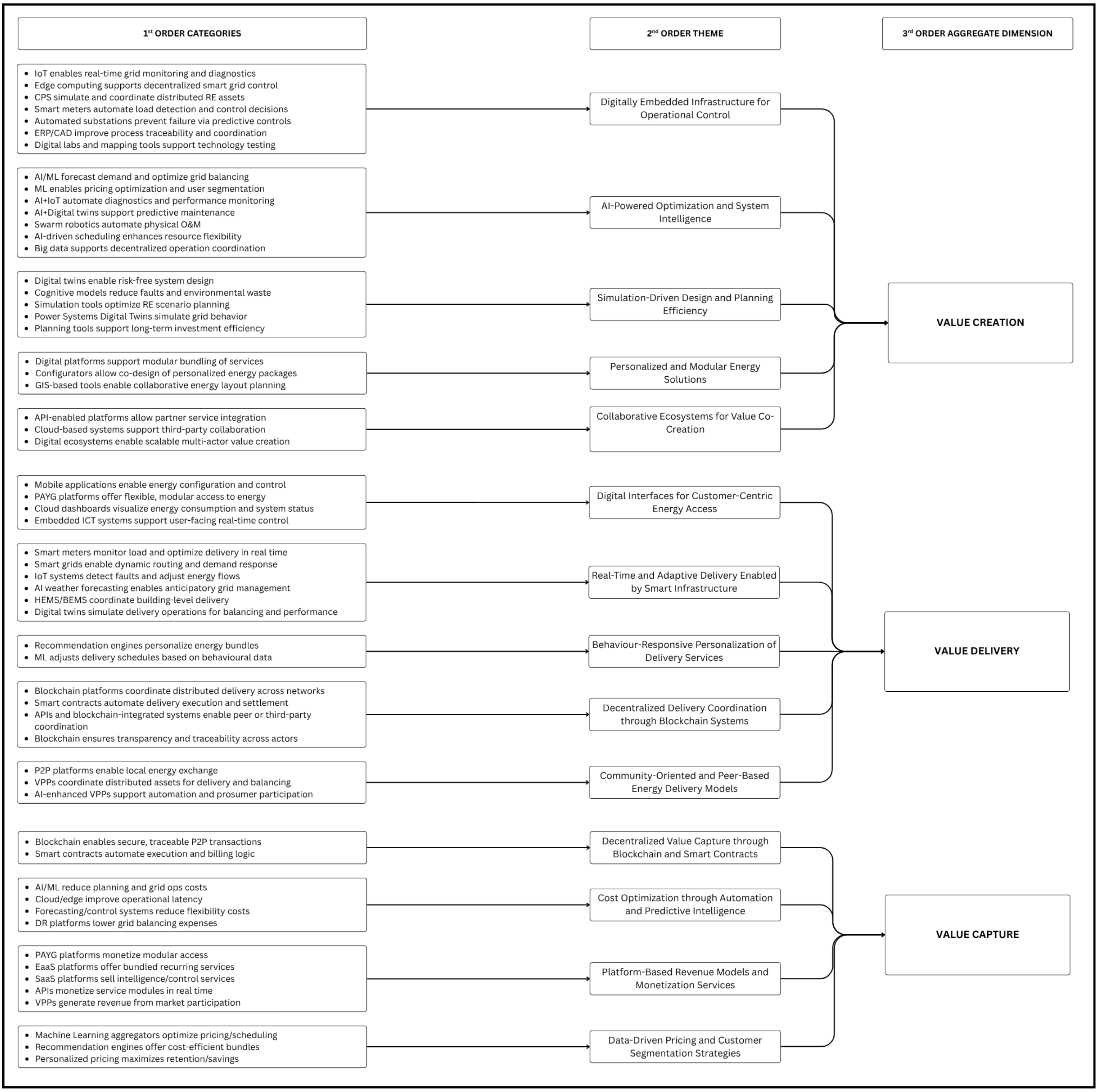

Figure 8. SLR Gioia Coding Structure of Business Model Components

Value Creation

Digitally Embedded Infrastructure for Operational Control

Digitally embedded infrastructure forms the operational backbone of renewable energy systems by enabling real-time monitoring, decentralized decision-making, and predictive control. Across the literature, technologies such as the Internet of Things (IoT), edge computing, cyber-physical systems (CPS), smart meters, automated substations, and ERP systems are identified as key enablers of system intelligence, responsiveness, and performance optimization.

IoT devices are central to this transformation, offering continuous data streams from distributed energy assets to enhance visibility, fault detection, load optimization, and grid stability. Ahmad et al. (2021) and Augello et al. (2022) emphasize that IoT integration improves real-time situational awareness and enables proactive diagnostics, while Adnan et al. (2024) highlight its role in reducing system downtime and supporting renewable integration in infrastructure-constrained regions. Edge computing further complements this by enabling localized data processing near the source, which reduces latency and allows for faster control responses, particularly critical in decentralized energy environments (Adnan et al., 2024).

Cyber-physical systems (CPS) extend these capabilities by providing synchronized digital models of physical energy systems. Through real-time simulations and control feedback loops, CPS architectures allow coordinated management of distributed generation assets and support experimentation with control strategies in risk-free environments (Adnan et al., 2024). Smart meters, also referred to as advanced metering infrastructure (AMI), contribute by automating load detection, enabling demand-responsive control, and facilitating granular consumption tracking and dynamic pricing strategies (Ahmad et al., 2021; Adnan et al., 2024).

At the grid infrastructure level, automated substations equipped with predictive analytics play a pivotal role in identifying faults in real time, minimizing equipment failure, and reducing operational downtime (Ahmad et al., 2021; Adnan et al., 2024). Supporting these systems on the backend, enterprise resource planning (ERP) tools serve as integrative platforms that align operational data with strategic control objectives. They improve traceability, standardize process coordination, and enable more efficient planning across organizational units (Del Vecchio et al., 2025).

Collectively, these digitally embedded technologies redefine the logic of value creation by transforming energy systems into adaptive, data-driven networks. They enable firms to operate more flexibly, reduce system inefficiencies, and proactively manage distributed energy assets, establishing a foundation for intelligent, scalable, and resilient renewable energy infrastructures.

AI-Powered Optimization and System Intelligence

The integration of artificial intelligence (AI), machine learning (ML), and big data analytics into renewable energy systems marks a significant shift in how operational intelligence is embedded within energy infrastructures. These technologies enable accurate forecasting, real-time control, predictive maintenance, and decentralized coordination, enhancing the value creation potential of digitalized energy systems.

AI and ML are particularly influential in energy forecasting and grid balancing. Ahmad et al. (2021) highlight their role in predicting renewable energy generation patterns and adjusting grid operations dynamically. Adnan et al. (2024) further illustrate how AI supports short-term system load forecasting and dispatch planning. In the Chinese context, digital forecasting tools have measurably improved renewable energy utilization rates by enhancing prediction accuracy and enabling responsive system adjustments (Zhao et al., 2021).

Beyond forecasting, AI technologies are increasingly used for market-facing activities such as dynamic pricing, demand segmentation, and personalized offerings. Vom Scheidt and Staudt (2024) present classification models that recommend personalized technology–tariff bundles based on user energy profiles, while Singh et al. (2021) note that energy startups in Germany employ ML to create customer-centric pricing and engagement strategies.

The convergence of AI and IoT further advances system intelligence through automated monitoring and diagnostics. Ahmad et al. (2021) describe how AI-enabled control systems embedded in smart grids can autonomously detect anomalies and adjust load flows in real time. Adnan et al. (2024) echo this by demonstrating how AI–IoT integration reduces operational downtime and enables predictive alerting for equipment maintenance.

A critical application of AI lies in its combination with digital twins for predictive infrastructure management. These twin systems simulate real-time behaviour of energy assets, integrating live data streams to enable performance optimization and fault prevention (Adnan et al., 2024; Yu et al., 2024). In addition, swarm intelligent robotics has been proposed as an emerging solution for automating the maintenance of renewable energy assets in inaccessible environments (Ahmad et al., 2021), though such technologies remain at an experimental stage.

Resource scheduling and system flexibility are also improved through AI-powered optimization engines. These tools facilitate adaptive load dispatch and help integrate intermittent energy sources more effectively (Ahmad et al., 2021; Adnan et al., 2024). Big data analytics serves as the backbone for these capabilities by enabling decentralized decision-making, market responsiveness, and granular control. Yu et al. (2024) and Ahmad et al. (2021) emphasize that analytics-driven decision support enhances coordination across actors and promotes strategic alignment with system-level innovation goals. Singh et al. (2021) further report that startups leverage ML and big data for high-resolution forecasting and performance tracking.

Together, these intelligent technologies contribute to value creation by embedding cognition, anticipation, and adaptability into the core of energy system operations. Firms are thus equipped to operate more efficiently, respond to market variability, and proactively manage distributed assets in an increasingly complex energy environment.

Simulation-Driven Design and Planning Efficiency

Simulation technologies, particularly Digital Twins (DTs), cognitive models, and scenario-based planning platforms, are increasingly central to value creation in renewable energy systems. These tools enable firms to test, forecast, and refine decisions digitally before committing physical resources, thereby supporting risk-free design, predictive maintenance, and long-term planning optimization.

Digital Twins serve as real-time virtual replicas of physical infrastructure, allowing operators to simulate asset performance, identify inefficiencies, and predict failures. D'Amore et al. (2022) demonstrate that AI-powered digital twins reduce operational downtime and costs by enabling virtual prototyping and proactive optimization across sectors such as energy, water, and agriculture. These simulations help decision-makers refine system configurations under different scenarios, accelerating design cycles while reducing material waste and resource consumption.

Further expanding on this capability, K. N. et al. (2024) highlight the use of digital twins in smart grid and green infrastructure applications. These tools facilitate early fault detection, real-time monitoring, and efficient load management. By creating data-rich virtual environments, digital twins enhance sustainability tracking and enable more informed infrastructure management without requiring extensive physical interventions.

Simulation modelling also supports decision-making at the operational level. Ciano et al. (2025) describe how digital twins embedded within process energy models contribute to intelligent energy management by improving energy efficiency and reducing waste. These simulations inform strategic decisions in smart manufacturing and energy systems by forecasting energy flows, optimizing operations, and supporting continuous system refinement.

A notable implementation of simulation-based planning is found in the Renewable Energy Valley (REV) initiative in Crete, as described by Skaloumpakas et al. (2024). In this case, Power Systems Digital Twins (PSDTs) are deployed to monitor and coordinate distributed energy resources across multiple local grids. PSDTs enable scenario-based simulations, support stakeholder collaboration, and improve grid reliability through virtual testing of infrastructure configurations and load behaviours. Their role in managing large volumes of sensor data also contributes to the efficient delivery of energy services and demand response coordination.

Together, these simulation technologies transform energy system design and planning by reducing uncertainty, enhancing real-time decision-making, and improving the long-term efficiency of infrastructure investments. By enabling virtual experimentation and predictive control, they allow firms to create more adaptive, sustainable, and cost-effective energy systems.

Personalized and Modular Energy Solutions

Digital technologies, particularly modular digital platforms, personalized configurators, and planning systems, are increasingly enabling energy firms to shift from standardized delivery models toward flexible, customer-centric solutions. These digital innovations allow users to participate in the design of their energy systems, choose bundled service offerings, and optimize infrastructure planning according to geographic and usage-specific needs.

Digital platforms are central to enabling modular bundling of services. As described by Hu et al. (2022), energy firms are increasingly adopting platform-based models that allow customers to select from a range of interconnected services, such as solar systems, storage, and monitoring tools, tailored to their unique consumption patterns. These platforms facilitate the orchestration of value streams beyond basic energy delivery, allowing for new revenue models and more resilient system configurations. Bartczak (2021) reinforces this by highlighting Digital Technology Platforms (DTPs) used in Polish energy markets, which enable real-time configuration of energy services and dynamic interaction among users, prosumers, and service providers. These platforms offer extensibility, modularity, and automation, forming the basis of customer-driven energy ecosystems. However, their reliance on continuous data flows also raises new risks in terms of cybersecurity and user privacy.

Personalized energy packages are increasingly enabled by configurators and AI-powered engagement tools. AI-based Customer Relationship Management (CRM) systems, as noted by Franki et al. (2023) and others, allow firms to unlock meter-level data and generate personalized recommendations based on consumption behaviour and payment patterns. These systems improve customer satisfaction, enhance segmentation strategies, and allow providers to tailor energy bundles for households, small businesses, or specific regional profiles. Predictive analytics and recommendation models are already being applied to match users with energy packages that optimize for efficiency, self-generation potential, and budget constraints (Ahmad et al., 2021; Vom Scheidt & Staudt, 2024).

Geographic customization is supported by digital planning and mapping tools that align energy infrastructure with local resource availability. While explicit references to GIS systems are limited, their functionality is evident in cases such as the Renewable Energy Valleys (REVs) in Crete. Skaloumpakas et al. (2024) describe how Power Systems Digital Twins (PSDTs) were deployed to simulate regional energy layouts, manage load balancing, and optimize infrastructure design. Similarly, Rasagam and Zhu (2018) emphasize the role of spatial planning and satellite-based assessments in aligning renewable energy access solutions with community-level needs in Sub-Saharan Africa. These tools enable planners to visualize optimal deployment zones, automate infrastructure routing, and anticipate future load requirements.

Together, these digital capabilities enable a more interactive and modular approach to energy system design. Platforms, configurators, and spatial planning tools collectively support personalized service delivery, flexible product bundling, and context-sensitive infrastructure planning, redefining how value is created and captured in digitally enabled renewable energy systems.

Collaborative Ecosystems for Value Co-Creation

Digitalization in the renewable energy sector is enabling the formation of collaborative ecosystems, where multiple actors, such as producers, prosumers, service providers, and technology developers, co-create value through interconnected digital infrastructures. These ecosystems are characterized by platform-based coordination, shared data environments, and service modularity.

Hu et al. (2022) document how a Chinese photovoltaic company transitioned from a traditional hardware supplier to a digital service platform. This shift enabled the integration of remote control tools, IoT systems, and partner interfaces, supporting new business relationships and cross-sector collaboration. The firm’s evolution illustrates how digital platforms can orchestrate value creation across multiple stakeholders rather than acting as isolated service channels.

Cloud-based systems further support this collaborative structure. Ahmad et al. (2021) highlight how cloud computing enhances smart grid coordination by enabling remote access, real-time responsiveness, and distributed control. These architectures, sometimes referred to as "energy clouds," help coordinate diverse actors and data flows, laying the groundwork for system-wide optimization and decentralized value delivery (Singh et al., 2021).

The broader concept of platform cooperativism, as described in the Cooperative Digital Platforms (2023) report, reflects the emergence of modular ecosystems where independent innovators, consumers, and infrastructure owners collectively manage shared assets and service modules. These digitally enabled ecosystems move beyond bilateral transactions to foster shared governance, value transparency, and flexible role participation.

Together, these developments illustrate how digital platforms and infrastructures are transforming value creation from firm-centric models to distributed, collaborative ecosystems, marking a significant shift in the business model logic of renewable energy firms.

Value Delivery

Digital Interfaces for Customer-Centric Energy Access

Digital interfaces such as mobile applications, cloud dashboards, and embedded ICT systems are central to enabling user-facing value delivery in renewable energy systems. These technologies enhance transparency, interactivity, and accessibility, particularly in distributed and off-grid contexts.

Mobile-based Pay-As-You-Go (PAYG) platforms have played a crucial role in extending energy access in underserved markets. Rasagam and Zhu (2018) highlight how companies like M-Kopa utilize mobile money and GSM-based systems to facilitate remote, credit-based energy consumption. These platforms offer a user-friendly access channel, allowing customers to activate and pay for energy services based on their financial capacity and usage needs. While they do not offer fine-grained consumption control, their digital accessibility represents a major advancement over traditional utility models.

Cloud-based dashboards further strengthen user engagement by providing real-time insights into energy usage and system status. Del Vecchio et al. (2025) and Zhao et al. (2021) emphasize the utility of these dashboards in visualizing consumption, detecting anomalies, and improving transparency. Gitelman and Kozhevnikov (2023) and Bähr and Fliaster (2023) discuss their application within Virtual Power Plant (VPP) frameworks, where user-facing platforms help prosumers monitor performance and contribute to grid flexibility. These visual tools support energy literacy and build trust between users and digital service providers.

Embedded ICT systems provide the infrastructure for responsive and personalized service delivery. As highlighted by Bartczak (2021), Plewnia (2019), Singh et al. (2021), and Pakulska and Poniatowska-Jaksch (2022), ICT integration enables features like remote system interaction, load monitoring, and real-time automation. These tools empower users to better understand and engage with their energy environment, marking a shift from passive consumption to active, interface-mediated participation.

Together, these digital interfaces improve the quality, flexibility, and transparency of value delivery in renewable energy systems. They bridge physical infrastructure with user engagement, enabling energy access that is not only more inclusive but also more intelligent.

Real-Time and Adaptive Delivery Enabled by Smart Infrastructure

Digitally enabled renewable energy systems increasingly rely on smart infrastructure to deliver electricity in real time, adapt to dynamic conditions, and optimize performance across distributed networks. Technologies such as smart meters, IoT platforms, AI forecasting systems, building-level energy management, and digital twins work in tandem to enable predictive, decentralized, and user-responsive value delivery.

Smart meters are a foundational technology for monitoring and optimizing energy delivery. As noted by Augello et al. (2022), their integration with IoT and edge computing enables decentralized grid responsiveness, improving real-time load monitoring and fault identification. Leiva Vilaplana et al. (2025) further highlight their role in automating delivery decisions by feeding granular consumption data into broader digital control systems. These smart meters support not just visibility but operational adaptability within smart grid infrastructures.

Smart grids equipped with real-time data interfaces allow for automated demand response and intelligent routing. Zhao et al. (2021) describe how digital layers embedded into grid infrastructure enhance system-wide monitoring and power maintenance. The combination of embedded sensors, communication systems, and control algorithms enables rapid identification of disruptions and seamless adaptation in power flows.

IoT-enabled fault detection systems also play a key role in adaptive delivery. Liu et al. (2024) and Augello et al. (2022) show how IoT platforms help detect system-level inefficiencies and allow for autonomous rebalancing, particularly when integrated with edge analytics. This supports real-time delivery adaptation without relying solely on centralized control.

AI-based weather and load forecasting further enhances anticipatory grid management. As highlighted by Adnan et al. (2024), Bartczak (2021), D'Amore et al. (2022), and Franki et al. (2023), AI models trained on historical and environmental data help operators predict energy generation fluctuations and adjust delivery schedules proactively. Neska and Kowalska-Pyzalska (2022) emphasize this in the context of HEMS, where local devices react to AI-derived forecasts for more efficient intra-building load balancing.

Building-level coordination systems, such as Home and Building Energy Management Systems (HEMS/BEMS), also support adaptive value delivery. Neska et al. (2022) detail how these systems manage consumption based on user behaviour, real-time prices, and system constraints. Vom Scheidt and Staudt (2024) complement this by showing how smart home platforms integrate device-level automation with broader energy system interfaces.

Finally, digital twins simulate energy delivery operations to enhance reliability and balance. As demonstrated by D'Amore et al. (2022), Adnan et al. (2024), and K.N. et al. (2024), digital twins create real-time models of infrastructure that allow operators to test delivery strategies and optimize grid balancing. Singh et al. (2021) and Ciano et al. (2025) note that such simulations are also key to aligning production, distribution, and user-facing systems in real time. Del Vecchio et al. (2025) adds that digital twin integration can support twin-transition goals, simultaneously improving energy and digital performance in delivery systems.

Together, these technologies enable a paradigm of adaptive, responsive, and intelligent energy delivery. Rather than static distribution models, firms now deploy infrastructure that learns, predicts, and adjusts, enhancing flexibility, system efficiency, and user satisfaction in renewable energy systems.

Behaviour-Responsive Personalization of Delivery Services

Digital technologies are enabling energy firms to personalize delivery by responding to user behaviour and consumption patterns. AI-powered recommendation engines, ML-based schedulers, and behavioural analytics help tailor energy bundles and delivery schedules, enhancing user experience and system efficiency.

Vom Scheidt and Staudt (2024) show how machine learning models match users with customized technology–tariff bundles based on their usage profiles. Singh et al. (2021) highlight how startups use digital platforms to continuously adapt services to behavioural data, improving flexibility and demand response.

Bartczak and Łobejko (2022) emphasize the role of Digital Technology Platforms (DTPs) in supporting modular delivery and user feedback loops. These platforms enable real-time personalization and co-creation of services. Ciano et al. (2025) add that home energy management systems (HEMS), powered by cloud-based analytics, track user behaviour to optimize delivery and provide individualized feedback.

Together, these tools shift value delivery from standardized supply to adaptive, user-responsive services, enhancing both customer satisfaction and grid responsiveness.

Decentralized Delivery Coordination through Blockchain Systems

Blockchain technologies are increasingly used to support decentralized coordination of energy delivery across distributed networks. By integrating smart contracts, traceability tools, and interoperable interfaces, these systems facilitate transparent, automated, and multi-actor delivery mechanisms.

Augello et al. (2022) and Mika et al. (2021) describe how blockchain platforms coordinate delivery across decentralized energy infrastructures, enabling trusted data exchange and reducing reliance on centralized control. These systems are particularly valuable in grid contexts where distributed actors require secure and auditable coordination mechanisms.

Smart contracts further extend blockchain functionality by automating delivery execution and settlement processes. As shown by Mika et al. (2021). and Gitelman and Kozhevnikov (2023), these contracts allow for seamless energy transactions, real-time verification, and reduced administrative overhead, supporting scalable peer-to-peer and aggregator-based service models.

Blockchain also enhances transparency and traceability across actors. Plewnia (2019) and Bartczak (2021) highlight how blockchain is used to record service flows, authenticate transactions, and align incentives across modular ecosystems. These functions are essential for building trust in systems where control is shared among users, service providers, and platforms.

In sum, blockchain technologies facilitate decentralized, automated, and transparent value delivery, particularly in systems where coordination and accountability must extend across diverse, digitally connected actors.

Community-Oriented and Peer-Based Energy Delivery Models

Community-based and peer-oriented digital delivery models are transforming how energy is exchanged, managed, and balanced at the local level. These models use platforms such as peer-to-peer (P2P) networks and Virtual Power Plants (VPPs) to coordinate distributed energy resources and foster prosumer participation.

P2P platforms facilitate direct energy exchange between users within local communities. As shown in studies like Mika et al. (2021) and Plewnia (2019), these systems leverage blockchain and IoT to automate transactions, record energy flows, and reduce dependence on centralized utilities. Skaloumpakas et al. (2024) highlight their use in community energy planning within Renewable Energy Valleys, enabling stakeholders to co-manage energy delivery based on localized data.

VPPs serve as digital infrastructures that coordinate multiple distributed assets, such as rooftop solar, batteries, and flexible loads, to function as unified delivery entities. Gitelman and Kozhevnikov (2023) and Bähr and Fliaster (2023) describe how VPPs enhance balancing and system reliability by aggregating prosumer contributions and adjusting in real time to grid conditions. These platforms promote cooperative value delivery while improving system efficiency.

AI further enhances VPP functionality by enabling real-time optimization and automation. As noted by Franki et al. (2023) and Bähr and Fliaster (2023), AI-powered diagnostics, forecasting, and dispatch systems support smart coordination of assets and enable active user participation.

Together, these digital models allow communities to take ownership of energy delivery while contributing to broader system stability. They enable more democratic, flexible, and resilient approaches to value delivery in the energy transition.

Value Capture

Decentralized Value Capture through Blockchain and Smart Contracts

Blockchain technologies and smart contracts are enabling decentralized, secure, and automated mechanisms for value capture in renewable energy systems. These tools facilitate traceable transactions, remove intermediaries, and enforce billing and settlement logic in peer-driven delivery models.

Blockchain’s core contribution lies in enabling secure and auditable peer-to-peer (P2P) energy transactions. As highlighted by Augello et al. (2022), blockchain platforms support decentralized coordination of distributed energy resources, particularly in demand response and prosumer environments. Mika et al.(2021) also emphasize blockchain's suitability for reducing reliance on centralized control systems by ensuring verifiability and resilience across distributed actors.

Smart contracts automate the execution of delivery agreements and billing procedures. Gitelman and Kozhevnikov (2023) show how these contracts streamline settlement processes and reduce transaction friction by codifying trust into programmable logic. Neska and Kowalska-Pyzalska (2022) add that smart contracts help enforce dynamic rules around prosumer participation and payment flows, making them central to decentralized business models.

K.N. et al. (2024) and Liu et al. (2024) further highlight how blockchain supports traceability in energy value chains, allowing stakeholders to monitor energy sources, transaction history, and sustainability claims, thereby enabling new forms of economic and environmental accountability. Singh et al. (2021) frame blockchain as a key enabler of platform-based value monetization by linking consumption data directly to distributed billing mechanisms.

Together, blockchain and smart contracts redefine value capture by shifting revenue logic from centralized utility collection to automated, peer-aligned, and tamper-proof transaction systems.

Cost Optimization through Automation and Predictive Intelligence

Digital technologies such as AI, ML, cloud computing, and demand response platforms are being widely used to reduce planning, operational, and flexibility costs in renewable energy systems. These tools enable predictive control, reduce manual intervention, and improve the economic efficiency of decentralized delivery models.

AI and ML-based forecasting tools are essential for cost reduction in grid operations. Franki et al. (2023) and D'Amore et al. (2022) show how predictive analytics improve planning efficiency, optimize dispatch, and minimize unplanned downtime. Skaloumpakas et al. (2024) reinforce this by describing how regional scenario modelling reduces system uncertainty and supports informed infrastructure investment.

Cloud and edge computing contribute to cost savings by improving response speed and reducing system latency. Adnan et al. (2024) highlight the use of edge-based control systems for local decision-making, which lowers coordination overhead and speeds up grid responsiveness.

Demand response (DR) platforms further lower grid balancing and flexibility costs. Augello et al. (2022) and Adnan et al. (2024) describe how intelligent DR tools automate load shifting and congestion management. Venkatachary et al. (2017) and Vom Scheidt and Staudt (2024) support this view by showcasing automated control in smart homes and community-level systems, reducing the need for expensive backup generation or overcapacity.

Together, these technologies help firms capture value by streamlining operations, reducing forecasting errors, and lowering the cost of decentralized energy delivery.

Platform-Based Revenue Models and Monetization Services

Digital platforms are increasingly central to value capture in renewable energy, enabling diverse monetization strategies such as subscription models, market participation, and real-time service modularization. These models reflect a shift from asset-based sales to service-based and data-driven revenue streams.

Pay-As-You-Go (PAYG) models provide flexible, modular access to solar energy services in underserved regions. As documented by Rasagam et al. (2018), mobile-integrated PAYG systems allow users to activate and pay for services incrementally, aligning revenue with consumption.

Energy-as-a-Service (EaaS) platforms bundle generation, storage, and digital monitoring into recurring service packages. Gitelman and Kozhevnikov (2023), K.N. et al. (2024), and Sulek et al. (2024) highlight how these models reduce upfront costs for users while creating stable, recurring income streams for providers.

Software-as-a-Service (SaaS) offerings generate revenue by selling digital intelligence, such as analytics, diagnostics, or automation, as standalone products. Pakulska and Poniatowska-Jaksch (2022) and Rasagam et al. (2018) emphasize how cloud-based platforms monetize optimization and control tools, especially in modular and B2B energy settings.

API-enabled platforms allow for real-time service modularization. Rasagam et al. (2018) notes that open architecture enables third-party integration and monetization of plug-and-play components such as diagnostics, billing, or monitoring interfaces.

Finally, Virtual Power Plants (VPPs) generate revenue by aggregating distributed assets and participating in wholesale markets. Bähr et al. (2023) and Venkatachary et al. (2017) show how AI-enhanced VPPs allow prosumers to monetize surplus generation and grid support services.

Together, these models reflect a digital reconfiguration of energy value capture, from selling electrons to orchestrating and monetizing services, intelligence, and user participation.

Data-Driven Pricing and Customer Segmentation Strategies

AI and ML technologies are increasingly used to personalize energy pricing and segment users based on consumption patterns, enabling firms to optimize revenue and customer satisfaction. These data-driven strategies align pricing with usage behaviour, flexibility potential, and system demand.

Vom Scheidt and Staudt (2024) demonstrate how ML-based aggregators and recommendation engines suggest personalized energy–tariff bundles. By analysing user load profiles and scheduling preferences, platforms can offer cost-efficient combinations that maximize system participation and user retention.

Adnan et al. (2024) highlight the role of AI and big data in optimizing grid operations and pricing schedules. These technologies enable more accurate forecasting of demand and supply, improving price responsiveness and reducing planning inefficiencies.

Bartczak (2021) and Franki et al. (2023) emphasize that personalized pricing increases user engagement while reducing churn and aligning costs with actual consumption. Liu et al. (2024) similarly note that dynamic pricing models, powered by behavioural analytics, unlock new monetization potential while enhancing customer loyalty.

Together, these approaches show how digital platforms are shifting from flat tariffs to intelligent, behaviour-sensitive pricing , making value capture more adaptive, granular, and user-aligned.

4.3.2 Digital Technologies Influencing on Business Model Change

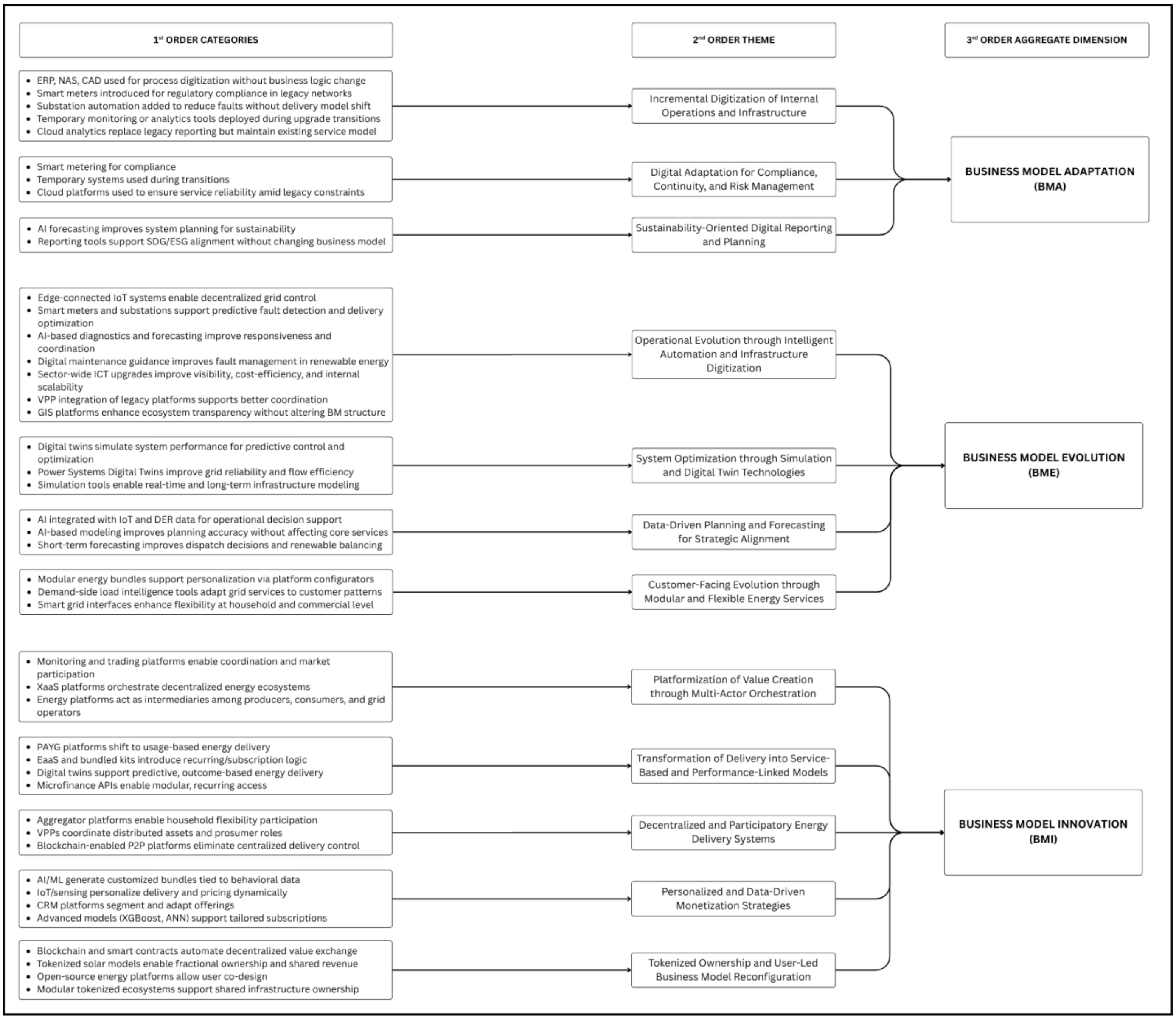

Figure 9. SLR Gioia Coding Structure of Business Model Change Types

Business Model Adaptation (BMA)

Incremental Digitization of Internal Operations and Infrastructure

Digitization efforts in the energy sector often focus on internal systems and infrastructure, aiming to improve operational efficiency and reduce risk without altering the core business model. These upgrades typically involve the integration of monitoring, automation, and enterprise systems that support existing workflows. Leiva Vilaplana et al. (2025) describe how substation automation was implemented in Portugal's distribution network to enhance fault detection and grid reliability. While technologically significant, such interventions maintained the existing service delivery model and customer relationships, representing incremental adaptation rather than transformation. Del Vecchio et al. (2025) similarly discuss the use of ERP and NAS tools in digital infrastructure upgrades, although their application is primarily linked to broader sustainability and performance goals.

Sustainability-Oriented Digital Reporting and Planning

Digital technologies are also applied in support of sustainability objectives without altering the underlying business model structure. Franki et al. (2023) describe how AI and big data are used for non-financial scenario analysis and alignment with Sustainable Development Goals (SDGs), particularly in energy infrastructure planning and resilience assessment. These tools improve long-term decision-making but do not affect how value is created, delivered, or captured. Similarly, Ciano et al. (2025) emphasize the role of cognitive digital twins in enabling strategic alignment with sustainability frameworks. By enhancing planning accuracy and tracking environmental performance, such tools contribute to compliance and positioning efforts, rather than business model transformation.

Business Model Evolution (BME)

Operational Evolution through Intelligent Automation and Infrastructure Digitization

Digitally enabled infrastructure upgrades are transforming how energy systems operate, improving coordination, responsiveness, and system reliability without radically shifting the business model logic. These transformations reflect Business Model Evolution (BME), where the underlying structure is retained but enhanced through embedded intelligence and decentralized control.

Augello et al. (2022) describe how IoT and edge technologies are deployed to enable decentralized grid control, allowing for more autonomous and responsive energy management. The integration of edge devices allow for local sensing and decision-making, enhancing operational flexibility without redefining value propositions.

Smart meters and substation automation also play a key role in operational evolution. As noted by Leiva Vilaplana et al. (2025), such infrastructure was implemented to improve grid monitoring and fault detection across Portugal’s DSO network. Plewnia (2019) and Augello et al. (2022) support this by highlighting how smart infrastructure increases system responsiveness and delivery efficiency without modifying service logic or customer relationships.

AI-based diagnostics and forecasting systems further enhance responsiveness and coordination. Franki et al. (2023) and Rasagam and Zhu (2018) describe the use of AI for intelligent dispatch and outage prediction, improving planning across distributed assets. Leiva et al. (2025) show how forecasting tools allow for improved load balancing in networked environments.

Del Vecchio et al. (2025) and Zhao et al. (2021) emphasize the use of digital maintenance platforms and scenario modelling to reduce faults and optimize system performance, again representing systemic evolution without a shift in business logic.

These upgrades exemplify BME: the system becomes more automated, predictive, and decentralized, but without transforming the core business model structure.

System Optimization through Simulation and Digital Twin Technologies

Digital twin and simulation technologies are increasingly adopted to enhance the performance, planning, and reliability of energy systems. These tools enable virtual testing, predictive modelling, and real-time infrastructure control, marking an evolutionary shift in how energy operations are coordinated, without altering the business model structure itself.

Adnan et al. (2024) describe how digital twins simulate renewable energy system performance to support predictive maintenance, load optimization, and operational efficiency. These simulations reduce downtime and improve resource allocation but do not introduce new value logics, fitting the characteristics of Business Model Evolution (BME).

Skaloumpakas et al. (2024) emphasize the role of Power Systems Digital Twins (PSDTs) in Renewable Energy Valleys, where digital models manage distributed energy resources and simulate grid behaviour. These systems help improve grid reliability and flow coordination while maintaining the existing service structure.

Ciano et al. (2025) and Singh et al. (2021) note how simulation tools, especially when integrated with cognitive modelling and AI, enhance long-term system planning and infrastructure design. These technologies enable firms to improve decision-making and risk management in renewable deployment without changing their delivery or capture models.

Together, these cases reflect how digital twins and simulation platforms drive operational optimization through enhanced digital capabilities, supporting BME by improving system-level intelligence while preserving the original business model logic.

Data-Driven Planning and Forecasting for Strategic Alignment

Artificial intelligence and forecasting systems are widely adopted across the energy sector to improve planning accuracy, dispatch decisions, and coordination of distributed energy resources (DERs). These technologies support strategic alignment and operational control without altering value propositions, service models, or monetization structures, placing them within the scope of Business Model Evolution (BME).

Ahmad et al. (2021) describe how AI is integrated with IoT and DER data to support decision-making in power network management, enabling better load forecasting and generation planning. These systems enhance grid responsiveness but do not shift the firm’s business logic.

Adnan et al. (2024) and Pakulska et al. (2022) highlight the role of AI-based modelling in improving planning precision, particularly under uncertainty. These digital tools optimize existing operations without restructuring how services are delivered or captured.

Franki et al. (2023) similarly show how machine learning applications help balance system load and plan for distributed asset coordination, enhancing forecasting resolution while maintaining the current business framework.

Venkatachary et al. (2017) and Zhao et al. (2021) discuss short-term forecasting tools used for renewable dispatch optimization. These systems improve the integration of intermittent resources and reduce operational inefficiencies, again enhancing performance without altering business model architecture.

Together, these cases reflect how data-driven tools reinforce existing operational and strategic capabilities, representing a clear case of business model evolution.

Customer-Facing Evolution through Modular and Flexible Energy Services

Digital technologies are increasingly used to enhance flexibility and responsiveness at the residential and commercial interface, enabling more adaptive energy service delivery without transforming the underlying business model. These developments align with Business Model Evolution (BME), where firms retain their core value structure while optimizing how services are delivered.

Cloud and edge computing systems are central to this shift. As described by Adnan et al. (2024), such platforms enable decentralized energy coordination by hosting digital twin simulations and processing real-time data from smart meters and field devices. These architectures improve latency, enhance local decision-making, and support flexible load management, all while maintaining existing revenue and service models.

Similarly, smart energy management systems (EMS) integrated with IoT sensors and optimization algorithms enhance responsiveness to customer demand. Ciano et al. (2025) and Zhao et al. (2021) emphasize how these technologies improve demand-side control, fault detection, and load shifting capabilities. An example is Siemens MindSphere, which was deployed to support residential and commercial grid flexibility through real-time sensor integration and adaptive relay tuning, demonstrating operational evolution without altering the business logic (Adnan et al, 2024).

These examples illustrate how customer-facing delivery mechanisms are evolving through modular, digital upgrades that optimize service flexibility while preserving the firm's existing business model structure.

Business Model Innovation (BMI)

Platformization of Value Creation through Multi-Actor Orchestration

Digital platforms are increasingly transforming energy value creation by orchestrating interactions among producers, consumers, grid operators, and service providers. These platforms shift the business model logic from firm-centric delivery to a decentralized, multi-actor ecosystem, characteristic of Business Model Innovation (BMI).

Rasagam and Zhu (2018) describe how mobile-integrated PAYG platforms act as digital infrastructure for remote solar delivery in Sub-Saharan Africa. These platforms combine metering, mobile payment, and modular energy access to facilitate real-time market participation, replacing traditional utility structures with user-driven coordination.

Plewina (2019) and Bartczak (2021) emphasize the role of monitoring and trading platforms in supporting peer-based energy services. These platforms introduce new data flows and interactions between distributed participants, enabling flexibility aggregation and prosumer contribution to local energy exchanges.

Singh et al. (2021) explore how Energy-as-a-Service (EaaS) and other XaaS platforms allow decentralized actors to access analytics, control systems, and billing as independent modules. This model supports new forms of value creation by separating service provision from asset ownership and enabling open participation.

Additionally, Pakulska et al. (2022) and Hu et al. (2022) highlight how digital energy platforms serve as intermediaries among producers, consumers, and regulatory stakeholders. These platforms facilitate real-time coordination, digital identity verification, and monetization of distributed services, fundamentally reshaping how value is created within the ecosystem.

Together, these cases reflect a shift toward platform-based orchestration of value, where the energy firm acts less as a sole provider and more as an enabler of transactions and services among multiple networked actors.

Transformation of Delivery into Service-Based and Performance-Linked Models

Digital technologies are reshaping how energy services are delivered by shifting from asset-based one-time sales to usage-based, recurring, and performance-linked delivery models. This represents a clear instance of Business Model Innovation (BMI), where not only technologies but also the underlying value logic is fundamentally altered.

Rasagam and Zhu (2018) illustrate how Pay-As-You-Go (PAYG) platforms in Sub-Saharan Africa redefine energy delivery by enabling prepaid, usage-based access to solar energy. These platforms allow customers to pay incrementally via mobile money, replacing traditional upfront ownership with flexible, recurring service.

Gitelman and Kozhevnikov (2023), K.N. et al. (2024), and Sulek et al. (2024) highlight the emergence of Energy-as-a-Service (EaaS) and bundled energy-appliance kits. These offerings combine power, hardware, and digital monitoring into subscription-based packages, allowing customers to access energy services without capital investment, while providers capture recurring revenue over time.

Performance-linked delivery is further supported by digital twin technologies. K.N. et al. (2024) and D'Amore et al. (2022) describe how digital twins simulate asset performance and enable predictive energy delivery based on real-time data. These models allow for outcome-based services, where system efficiency, not asset ownership, defines the basis for value capture.

Rasagam and Zhu (2018) also emphasize the role of microfinance APIs integrated into PAYG platforms, which allow users to unlock modular upgrades and maintain recurring access, reinforcing the transition to flexible, customer-aligned delivery models.

These developments collectively signal a shift toward digitally enabled, service-oriented business models in energy, where delivery is ongoing, responsive, and deeply integrated with data and platform logic.

Decentralized and Participatory Energy Delivery Systems

Digital technologies are enabling a transition from centralized delivery models to decentralized, participatory systems, where users, particularly prosumers, play an active role in energy delivery and grid coordination. These shifts constitute Business Model Innovation (BMI), as they introduce fundamentally new logic around actor roles, coordination, and value creation.

Virtual Power Plants (VPPs) are a central mechanism in this transition. As described by Gitelman and Kozhevnikov (2023), VPPs aggregate distributed assets such as rooftop solar, batteries, and smart appliances, coordinating their output as a single, flexible resource. Bähr et al. (2023) and Venkatachary et al. (2017) emphasize how VPPs enable household participation in grid markets, transforming consumers into dynamic system actors. Franki et al. (2023) highlight how AI-enhanced VPPs optimize dispatch and flexibility management, automating complex coordination functions that were previously centrally controlled.

In parallel, blockchain-enabled peer-to-peer (P2P) platforms eliminate the need for centralized intermediaries by allowing direct energy exchange among participants. Mika et al. (2021) and Neska and Kowalska-Pyzalska (2022) describe how blockchain ensures traceability, trust, and automated settlement between households, enabling fully decentralized control of delivery flows and market participation.

These platforms redefine how energy systems operate, shifting control, trust, and value exchange from utilities to users and ecosystems. Such participatory structures reflect a new business model logic in which value is co-created across decentralized, digitally mediated networks.

Personalized and Data-Driven Monetization Strategies

Artificial intelligence, machine learning, and sensor-driven platforms are driving a transition toward individualized monetization strategies in the energy sector. Rather than offering standardized pricing or fixed tariffs, energy firms are increasingly using digital technologies to generate customized bundles, dynamic pricing models, and subscription-based services, constituting a clear case of Business Model Innovation (BMI).

Augello et al. (2022) describe how the integration of IoT and edge devices enables smarter, decentralized grids that can respond to real-time consumption data. These capabilities lay the foundation for dynamically tailoring services to user behaviours and energy demand patterns. Similarly, Bartczak (2021) discusses how AI and behavioural profiling are applied to support personalized service design and modular bundling, moving beyond static offers to more customer-specific packages.

Customer segmentation is also transformed through advanced CRM systems powered by data analytics. Franki et al. (2023) emphasize that AI-enabled customer engagement tools allow firms to track meter-level consumption data, detect behavioural signals, and personalize offers to maximize retention and energy efficiency.

Further, Vom Scheidt and Staudt (2024) describe the use of machine learning models, including algorithms like XGBoost and artificial neural networks (ANNs), to recommend technology–tariff bundles based on individual household profiles. These tools support subscription-based energy delivery, where bundles are generated not only based on device compatibility but also behavioural and load data, representing a shift toward fully data-driven value capture.

Together, these developments show how digital platforms and analytics are reshaping monetization logic by embedding intelligence and personalization into pricing, bundling, and customer interaction models.

Tokenized Ownership and User-Led Business Model Reconfiguration

Recent developments in blockchain and open-source digital infrastructures are enabling business model innovations that redistribute ownership, control, and value capture to end-users. These models replace centralized service logic with participatory, token-driven ecosystems, marking a transformative shift in business model logic.

Mika et al. (2021) describe how tokenized solar models allow users to purchase fractional ownership in renewable energy systems, enabling them to participate directly in revenue generation and asset governance. This disintermediation challenges traditional utility roles and allows for decentralized, community-based investment and payout models.

Neska and Kowalska-Pyzalska (2022) and Gitelman and Kozhevnikov (2023) highlight how blockchain and smart contracts support automated, decentralized value exchange among prosumers and service providers. These technologies enforce trust, streamline transactions, and enable direct market access, removing the need for centralized billing or grid coordination.

Bartczak (2022) explores open-source digital platforms that allow users to co-design and customize energy service modules. These platforms decentralize not only control but also the process of service development, creating space for participatory business logic where users contribute to system evolution.

Plewina (2019) further discusses modular blockchain-based ecosystems where users share ownership of infrastructure and service modules through token-based systems. These cooperative structures enable dynamic participation and flexible redistribution of value, reshaping traditional boundaries between producer, consumer, and operator.

Together, these innovations represent a radical shift in how value is created, distributed, and governed, characteristic of Business Model Innovation (BMI) rooted in participatory, tokenized, and open digital ecosystems.

4.4 Technology Trigger Analysis: Grouping Digital Technologies by Functional Role

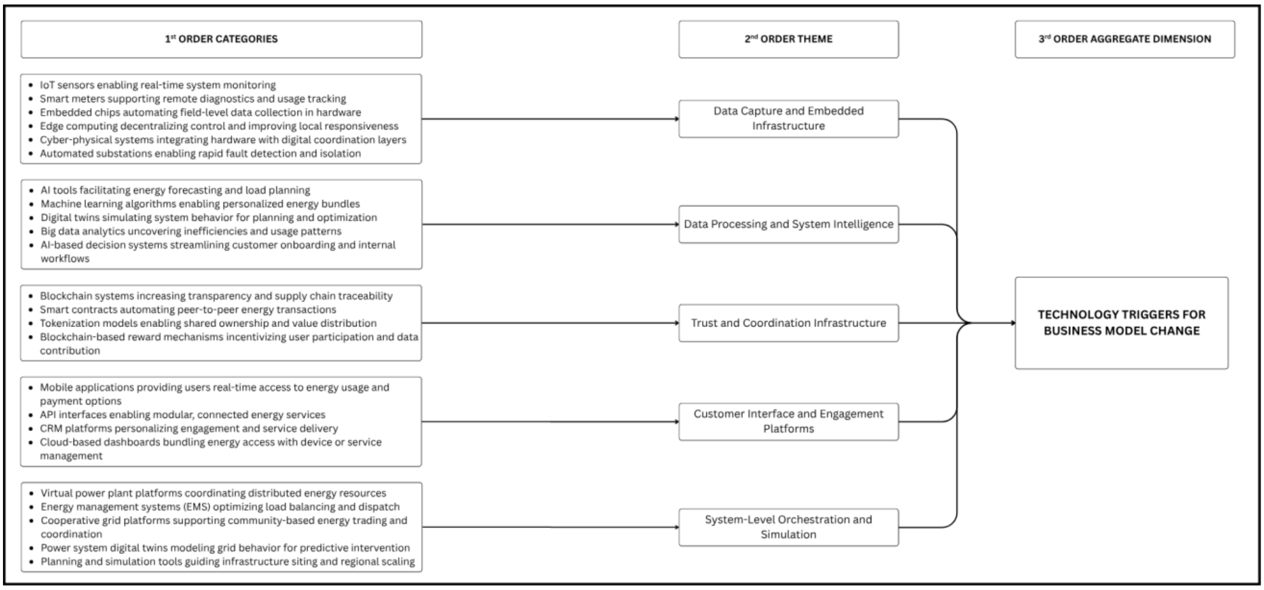

Figure 10. Functional Grouping of Digital Technologies as Triggers for Business Model Change

This section presents a cross-case synthesis of the digital technologies identified in both the interviews and the systematic literature review. While the preceding sections focused on how digital technologies influence specific components of the business model, this analysis groups technologies based on their observed functional role in triggering business model change. Using the Gioia methodology, individual technologies were coded as first-order categories, then clustered into higher-level second-order themes. These themes represent recurring technological roles , for example, enabling sensing, processing, personalization, or system-level coordination , that firms used as entry points into broader business model transformation. All of these contribute to the overarching aggregate dimension of Technology Triggers for Business Model Change.

The resulting Gioia Tree (Figure 8) includes five second-order categories: Data Capture and Embedded Infrastructure, Data Processing and System Intelligence, Trust and Coordination Infrastructure, Customer Interface and Engagement Platforms, and System-Level Orchestration and Simulation. These functional groupings help clarify not only which technologies were used, but also why and how they were deployed to initiate or support changes in business model structure.

These five functional roles are used in Section 5.1.3 to examine how digital technologies are interpreted and deployed by firms, and how they differentially influence business model components - namely value creation, value delivery, and value capture. While later sections explore patterns of business model change (BMA, BME, BMI), the groupings here serve primarily to explain how various digital tools act as triggers that reshape individual elements within the business model framework.

5 Discussions and Limitations

This chapter brings together findings from the five interview cases and the systematic literature review (SLR) to understand how digital technologies influence business model change in renewable energy firms. It compares patterns across the cases, identifies key differences and similarities, and reflects on how these changes align with concepts such as adaptation, evolution, and innovation. By linking case-level insights with broader trends from the literature, the chapter provides a more complete picture of digital transformation in the sector.

While this combined analysis reveals strong thematic alignment between the two datasets, it is shaped by the predominance of solar-related technologies in both sources. Coverage of other renewable energy sectors such as wind, hydrogen, or tidal power is limited, which may mean that sector-specific technology functions or configurations are underrepresented. Future research could test whether the patterns and relationships identified here hold across a broader range of renewable contexts.

5.1 Key Digital Technologies and Observed Patterns

This section addresses the first sub-question of the study:
Which digital technologies are being used by renewable energy firms?

5.1.1 Insights from Interviews

Across the five firms studied, digital technologies play a central role in shaping operations, enabling strategic flexibility, and in some cases, laying the foundation for entirely new business models. While the adoption contexts vary across firms, four categories of digital technologies emerged prominently: Artificial Intelligence (AI), Internet of Things (IoT), Blockchain, and Cloud-based platforms, which also include mobile apps, SaaS tools, and dashboards. Each technology serves different purposes across firms, ranging from enhancing operational efficiency to supporting monetization strategies, reflecting the diversity in digital maturity and strategic focus among the cases.

Artificial Intelligence (AI) was the most frequently discussed technology across firms, applied in both internal operations and customer-facing functionalities. Firm A described portfolio companies using AI for real-time forecasting and optimization of energy procurement in the spot market. Firm D highlighted how AI tools significantly accelerated their software development processes, allowing them to bring new offerings to market faster with fewer resources. In Firm C, AI and machine learning are embedded into the system to analyse panel-level data and detect patterns such as anomalies in battery degradation. Firm E is developing AI-supported onboarding processes that dynamically generate customer questions based on previous responses. These examples show that AI is used not only to automate internal processes, but also to support advanced data analytics, customer personalization, and strategic responsiveness.

Internet of Things (IoT) technologies are widely used across Firms A, B, C, and E. In Firm C, IoT sensors and smart chips are embedded into solar panels to enable real-time data collection and automated diagnostics. Firm B uses Raspberry Pi and Modebus-based sensor systems to monitor performance and support predictive maintenance for circular PV modules. Firm E relies on IoT infrastructure to remotely monitor modular solar systems and to track customer usage, which feeds into ongoing system improvements and troubleshooting. In Firm A's portfolio, IoT-enabled heating control systems and energy meters are used for demand-side optimization. These examples demonstrate that IoT is not just a support layer but is often integral to the firm's physical offering and value logic, especially where traceability, monitoring, and decentralized energy deployment are concerned.

Blockchain is used more selectively but in strategically significant ways by Firms B and C. Firm B integrates blockchain via a partnership with Circularise to implement digital product passports for traceability and circularity compliance. This enables end-users and partners to verify the lifecycle and material origin of solar components. Firm C, on the other hand, has embedded blockchain deeper into its platform architecture, supporting digital identity for solar panels, enabling peer-to-peer (P2P) energy trading, and developing tokenized yield distribution models for solar park investors. In both cases, blockchain serves as an infrastructure for trust, transparency, and decentralization, supporting new forms of value creation and delivery that go beyond traditional hardware-based business models.

Cloud-based platforms, SaaS solutions, and mobile apps are another foundational technology cluster used across Firms A, C, D, and E. Firm D operates a fully cloud-based energy simulation tool using digital twin technology, enabling consultants and EPCs to co-design energy systems in a scalable, interactive environment. Firm C provides APIs and a mobile app that allow users and third-party stakeholders (e.g., insurers, grid operators) to interact with verified system performance data in real time. Firm E employs mobile dashboards to facilitate its pay-as-you-go (PAYGO) delivery model, enabling energy access in remote and infrastructure-constrained markets. Meanwhile, Firm A reported that many of its portfolio companies offer white-labelled SaaS platforms for utility clients, reflecting broader industry-wide shifts toward modular, software-defined energy services.

Together, these observations reveal that while firms often use similar categories of technology, the degree of integration, purpose of use, and architectural depth differ considerably. AI may be used in one firm to automate internal workflows, while in another it supports customer onboarding or predictive maintenance. Blockchain may enable simple traceability in one context and programmable asset monetization in another. These differences set the stage for analysing how digital technologies affect business model components, and whether such changes lead to adaptation, evolution, or innovation.

Table 4 below summarizes the technologies currently implemented across the five case firms. This table complements the narrative analysis by offering a comparative view of digital technology footprints and supports further discussion in Section 5.2 on how these tools shape specific business model components.

Table 4. Technology Adoption Across Firms

Firm	AI	IoT	Blockchain	Cloud/Mobile/SaaS
Firm A	✓	✓	✗	✓
Firm B	✗	✓	✓	✗
Firm C	✓	✓	✓	✓
Firm D	✓	✗	✗	✓
Firm E	✓	✓	✗	✓

5.1.2 Insights from the Systematic Literature Review (SLR)

This section complements the interview-based analysis by presenting key patterns in digital technology usage as observed across the 29 academic studies included in the systematic literature review. The aim is to contrast how digital technologies are framed and conceptualized in academic discourse relative to the more grounded and context-specific insights from the case firms.

A notable strength of the literature dataset is its breadth and diversity. Unlike the interviews, which focus on a limited number of firms operating within particular market or infrastructural constraints, the literature captures generalizable trends, experimental deployments, and innovation trajectories across varied geographies and actors. This allows for a more holistic view of how digital technologies are shaping the energy sector over time (Franki et al., 2023; Gitelman & Kozhevnikov, 2023; Singh et al., 2021).

Across the reviewed studies, digital technologies are portrayed as core enablers of intelligent, adaptive, and decentralized energy systems. Technologies such as artificial intelligence (AI), Internet of Things (IoT), blockchain, and digital twins are discussed not in isolation but as part of interdependent digital architectures. These architectures are designed to support functions such as predictive control, multi-actor coordination, user engagement, and system-level planning (Adnan et al., 2024; Ahmad et al., 2021).

AI and machine learning are commonly associated with forecasting, predictive maintenance, and customer segmentation (Vom Scheidt & Staudt, 2024; Singh et al., 2021). For instance, AI-enabled forecasting tools improve the accuracy of load balancing and dispatch decisions (Franki et al., 2023; Zhao et al., 2021), while machine learning algorithms generate personalized energy–tariff bundles that optimize both customer experience and system efficiency (Vom Scheidt & Staudt, 2024).

IoT forms the sensory backbone of digital infrastructure by enabling real-time monitoring, fault detection, and load optimization at the device and grid levels (Ahmad et al., 2021; Adnan et al., 2024; Leiva Vilaplana et al., 2025). Edge computing is often paired with IoT to reduce latency and support decentralized decision-making (Adnan et al., 2024; Augello et al., 2022).

Blockchain and smart contracts are highlighted for enabling decentralized trust mechanisms, peer-to-peer (P2P) transactions, and tokenized asset management (Mika et al., 2021; Neska & Kowalska-Pyzalska, 2022; Gitelman & Kozhevnikov, 2023). These technologies facilitate secure, auditable exchanges between distributed actors, reduce reliance on centralized utilities, and support the emergence of community-managed service models.

Meanwhile, digital twins and simulation tools are shown to improve operational reliability, reduce planning uncertainty, and facilitate long-term scenario modelling (D'Amore et al., 2022; Ciano et al., 2025; Skaloumpakas et al., 2024). In particular, power systems digital twins (PSDTs) enable real-time coordination and predictive control across distributed assets in smart grid environments (KN et al., 2024; Singh et al., 2021).

An important distinction is that the literature tends to adopt a forward-looking perspective, emphasizing the potential of digital technologies to reshape business models and sectoral dynamics. While real-world implementation may still be limited in some cases, the academic discourse often frames digitalization as a systemic shift, one that encompasses not only technical change but also institutional, social, and economic redesign (Cooperative Digital Platforms, 2023; Gitelman & Kozhevnikov, 2023; Bähr & Fliaster, 2023). For example, cooperative digital platforms are presented as emerging governance models that enable shared asset ownership and participatory energy planning (Cooperative Digital Platforms, 2023), while modular energy-as-a-service models and token-based ownership systems introduce new revenue logics and actor roles (Mika et al., 2021; Rasagam & Zhu, 2018).

Several studies also highlight the convergence of digital technologies, particularly how AI, blockchain, and IoT interact to support dynamic pricing, automated service delivery, and personalized energy experiences (Bartczak, 2021; Franki et al., 2023; Singh et al., 2021). This layered use of technologies points to a shift away from single-point applications and toward holistic, data-driven ecosystems.

To enable more structured interpretation in the following sections, the diverse digital technologies identified in the literature are categorized into five overarching functional groups. These groupings, introduced in Section 5.1.3, serve as a conceptual bridge between the technological landscape outlined here and the subsequent analysis of how these technologies influence business model components and transformation types.

In addition to widely adopted technologies like AI, IoT, blockchain, and digital twins, the literature also discusses several emerging or speculative technologies that did not appear in the interview dataset. These include augmented and virtual reality (AR/VR), metaverse environments, quantum computing, and distributed computing architectures. While these tools are often positioned as potential enablers of immersive planning, enhanced grid optimization, or future decentralized ecosystems, their practical application in renewable energy firms remains limited at this stage. Their mention in the literature typically occurs within forward-looking or conceptual studies rather than grounded empirical implementations. This divergence suggests that while the academic discourse is expanding into new digital frontiers, the current realities faced by high-tech energy firms remain more focused on immediate, interoperable technologies that address present-day operational and market challenges.

5.1.3 Grouped Technology Categories and Observed Roles

To make sense of the diverse digital technologies identified across interviews and the literature, this section organizes them into five broad groups based on their main purpose in renewable energy firms. These groups reflect how technologies are being used in practice, to collect data, process information, build trust, interact with customers, and coordinate systems. These groupings are not mutually exclusive. In practice, firms often combine technologies across multiple groups to configure layered digital architectures, each supporting different dimensions of value creation, delivery, and capture.

Why functional groups matter? In this study, technologies from both the interviews and the systematic literature review are clustered by function rather than by individual technology names or market classifications. This integrated grouping reduces construct overload, makes patterns across firms and contexts comparable, and links directly to business model components by clarifying how data moves from collection to processing and integration, and then to orchestration. This grouping also provides a clear link between the technologies identified and the specific business model components they influence, as shown in our findings where data collection layers were most prominent in value creation, processing and integration layers in value delivery, and orchestration layers in value capture.

The groupings were derived through a cross-case synthesis of digital technologies observed across the interview and literature datasets, as presented in Section 4.4. Using the Gioia methodology, individual technologies were clustered into higher-order themes based on their functional role in triggering business model change. This structure serves as an analytical foundation for the comparative interpretation that follows.

Group 1: Data Capture and Embedded Infrastructure
This group includes technologies that enable real-time system visibility, diagnostics, and control. From the interviews, IoT sensors, smart meters, and embedded chips were widely used across Firms B, C, and E to support solar asset monitoring, performance optimization, and remote troubleshooting. Literature sources further extended this group to include edge computing, automated substations, and cyber-physical systems (Ahmad et al., 2021; Adnan et al., 2024; Leiva Vilaplana et al., 2025). These technologies form the foundational layer for collecting data and translating physical system states into digital inputs.

Group 2: Data Processing and System Intelligence
Technologies in this group, such as AI, ML, big data analytics, and digital twins, are used to analyze, predict, and optimize operations. In interviews, AI was mentioned across all firms except B, applied for forecasting (Firm A), onboarding (Firm E), diagnostics (Firm C), and software acceleration (Firm D). In the literature, these tools support use cases like predictive maintenance (Franki et al., 2023), personalized energy bundles (Vom Scheidt & Staudt, 2024), and planning simulations (Ciano et al., 2025; D'Amore et al., 2022). Digital twins serve a dual role, real-time system simulation and long-term planning, which ties this group to both operational control and strategic decision-making.

Group 3: Trust and Coordination Infrastructure
This group includes blockchain, smart contracts, and related tools that enable decentralized, verifiable, and programmable energy transactions. Firm B used blockchain for traceability through Circularise, while Firm C integrated it deeply for digital identity, tokenized yield distribution, and P2P trading. In the literature, blockchain was linked to enabling fractional

ownership (Mika et al., 2021), P2P coordination (Neska & Kowalska-Pyzalska, 2022), and automated settlement mechanisms (Gitelman & Kozhevnikov, 2023). These technologies are critical where transparency, trust, or distributed control are central to the business model.

Group 4: Customer Interface and Engagement Platforms
This group includes mobile apps, cloud dashboards, SaaS tools, APIs, and AI-driven CRM platforms. These technologies serve as the interactive layer through which users access services, make payments, monitor usage, and receive personalized content. Firm D's SaaS interface for energy simulations, Firm E's PAYGO mobile dashboard, and Firm C's integrated user-operator dashboards are all examples. From the literature, Rasagam & Zhu (2018) and Singh et al. (2021) highlight how mobile apps and configurators enhance accessibility and real-time interaction in decentralized markets. This group is particularly relevant to value delivery and personalization.

Group 5: System-Level Orchestration and Simulation
These technologies coordinate distributed actors and assets, often at ecosystem scale. Examples include energy management systems (EMS), virtual power plants (VPPs), power systems digital twins (PSDTs), cooperative platforms, and spatial planning tools. While Firms C and D hinted at such orchestration through APIs and cloud-based simulation, the literature provided stronger evidence of these technologies being used to coordinate grid operations, community energy systems, and regional deployment scenarios (Skaloumpakas et al., 2024; K.N. et al., 2024; Cooperative Digital Platforms, 2023). These tools are essential for enabling multi-actor coordination, flexible load balancing, and long-term energy planning.
Taken together, these five functional groups provide a high-level view of how digital technologies contribute to the reconfiguration of business model logic in the renewable energy sector. They also help explain why certain technologies may have greater influence on specific components, such as how Group 1 supports operational efficiency (value creation), Group 4 enhances service flexibility (value delivery), or Group 3 enables new monetization models (value capture).

Table 5 below provides an overview of the five functional technology categories, the specific tools they include, their primary business roles, and representative citations from the literature.

Table 5. Grouping of Digital Technologies Identified in the Literature and Interviews

Functional Group	Key Technologies	Primary Roles Observed
1. Data Capture and Embedded Infrastructure	IoT devices, smart meters, CPS, edge computing, automated substations	Real-time visibility, system monitoring, decentralized sensing, load optimization
2. Data Processing and System Intelligence	AI, ML, big data analytics, digital twins, swarm intelligence	Forecasting, predictive maintenance, simulation, optimization, automation, personalization
3. Trust and Coordination Infrastructure	Blockchain, smart contracts, tokenization, digital identity systems	Decentralized transactions, P2P trading, traceability, fractional ownership
4. Customer Interface and Engagement Platforms	Mobile apps, SaaS dashboards, APIs, CRM systems, configurators	User interaction, PAYGO models, usage tracking, service modularization, personalization
5. System-Level Orchestration and Simulation	EMS, PSDTs, VPPs, cooperative platforms, GIS/spatial planning tools	Multi-actor coordination, system balancing, community governance, geospatial infrastructure planning

5.2 Digital Technologies' Influence on Business Model Components

This section addresses the second sub-question of the study:
How does digitalization impact the individual components of business models-value creation, value delivery, and value capture-in these firms?

Building on the detailed analysis in Chapter 4, this section provides a cross-case synthesis of how digital technologies interact with the foundational components of business models. We use the above cross-dataset functional grouping to trace component-level effects.

5.2.1 Digital Technologies and Value Creation

Digital technologies play a central role in transforming how renewable energy firms create value. This component, focused on the activities and resources used to generate benefits for customers and stakeholders, was the most extensively reconfigured across both interviews and literature. Two primary patterns emerged:

1. Digital optimization of core activities and infrastructure, and
2. Expansion of value creation through data-enabled, co-created services.

Insights from Interviews:

Across the cases, firms deployed digital technologies to automate processes, embed intelligence, and generate new forms of value. AI supported operational forecasting (Firm A), accelerated product development (Firm D), and enhanced customer onboarding (Firm E). IoT infrastructure, used by Firms B, C, and E, enabled real-time monitoring, predictive maintenance, and remote diagnostics.

The most advanced form was seen in Firm C, which integrated IoT, AI, and blockchain to provide "data-as-a-service" via a digital platform. Verified performance data became a monetizable asset for partners like insurers and grid operators. Firm B used blockchain to enable product traceability aligned with its circular value proposition, though this remained more compliance-driven.

These cases illustrate how digitalization enables both internal efficiency and external value co-creation, marking a shift from product delivery to data-based, participatory services.

Insights from the SLR:

The literature echoed and extended these patterns. Technologies such as IoT, CPS, and edge computing support real-time visibility and system optimization (Ahmad et al., 2021; Leiva Vilaplana et al., 2025; Adnan et al., 2024). AI and ML enable predictive maintenance, personalized services, and adaptive load balancing (Franki et al., 2023; Vom Scheidt & Staudt, 2024). Digital twins support both real-time simulation and scenario-based planning (Ciano et al., 2025; D'Amore et al., 2022).

Planning platforms like GIS tools optimize deployment in resource-constrained areas (Rasagam & Zhu, 2018), while early-stage applications of swarm intelligence suggest a future path toward autonomous operations (Ahmad et al., 2021).

Synthesis and Cross-Case Themes:

Despite varying contexts, two consistent patterns define digital value creation across both datasets. First, digitally embedded infrastructure, such as IoT, smart meters, and cyber-physical systems, forms the operational backbone for system visibility, control, and responsiveness. Second, AI-driven system intelligence transforms value creation from reactive to predictive, enabling scenario planning, automation, and dynamic customization. Third, secure data coordination mechanisms, such as blockchain, extend value creation beyond the firm by making system outputs verifiable, trusted, and usable for external stakeholders.

Viewed through the lens of technology groupings, these patterns are primarily enabled by three functional clusters.

- Group 1: Data Capture and Embedded Infrastructure reinforces key resources and operational processes by embedding real-time sensing and diagnostics into physical systems.
- Group 2: Data Processing and System Intelligence strengthens key activities through forecasting, optimization, and intelligent control.
- Group 3: Trust and Coordination Infrastructure extends the value proposition by making performance data verifiable, usable, and exchangeable across stakeholders.

Together, these mechanisms illustrate how digital technologies serve as layered triggers that reconfigure value creation in high-tech renewable energy firms, enabling the shift from asset-based to data-driven and collaborative service models.

5.2.2 Digital Technologies and Value Delivery

Digitalization is redefining how renewable energy firms deliver value, shifting from static, physical channels to dynamic, digitally mediated systems. Value delivery now occurs through interfaces, platforms, and coordination mechanisms that support real-time, multi-actor interaction. Three recurring patterns were observed:

1. Interface transformation and remote accessibility,
2. Real-time coordination and adaptive delivery, and
3. Participatory, decentralized delivery structures.

Insights from Interviews:

Case firms used a range of digital tools to restructure how services reach users and partners. Firm D moved from on-site consultancy to a cloud-based simulation platform, enabling self-service co-design. Firm E adopted a mobile PAYGO model, allowing off-grid users to manage energy access and payments via smartphones.

Firm C developed a multi-interface ecosystem, including APIs, blockchain wallets, and mobile dashboards, for stakeholders like grid operators and insurers to interact with real-time performance data. Startups in Firm A's portfolio employed SaaS dashboards for energy monitoring, billing, and segmentation.

Collectively, these cases illustrate a transition to digitally managed, interactive, and scalable delivery systems, tailored to user behaviour and external conditions.

Insights from the SLR:

The literature confirms these patterns and adds system-level depth. Mobile apps and SaaS platforms support PAYGO models and user transparency (Rasagam & Zhu, 2018; Zhao et al., 2021). Smart meters and edge computing enable automated delivery adjustments in response to load changes and market signals (Ahmad et al., 2021; Leiva Vilaplana et al., 2025).

Digital twins support predictive delivery coordination, especially in environments like VPPs that require real-time orchestration of distributed assets (Ciano et al., 2025; KN et al., 2024). AI tools track user behaviour and adjust service levels accordingly (Vom Scheidt & Staudt, 2024), while blockchain and smart contracts automate decentralized service agreements (Mika et al., 2021; Neska & Kowalska-Pyzalska, 2022).

Synthesis and Cross-Case Themes:

Across both datasets, value delivery is increasingly shaped by digital infrastructure that supports interactive, adaptive, and multi-stakeholder service experiences. Firms are moving away from fixed, physical delivery modes toward more flexible, user-centered approaches.

Interface-based platforms allow asynchronous access and personalization; intelligent systems enable dynamic service coordination; and decentralized technologies allow users to co-manage delivery alongside providers.

Viewed through the lens of technology groupings, these shifts are primarily enabled by three key clusters:

- Group 4: Customer Interface and Engagement Platforms directly reconfigure customer channels and relationships, enabling on-demand service access, real-time feedback, and mobile-based energy interactions.
- Group 2: Data Processing and System Intelligence enhances service configuration and delivery timing, using forecasting, user segmentation, and behavioural adaptation to align service outputs with dynamic demand.
- Group 5: System-Level Orchestration and Simulation enables coordination across partner networks and operational layers, allowing real-time delivery adjustments, automated balancing, and virtual asset management across decentralized systems.

Together, these technologies shift value delivery from a one-way transaction to a flexible, co-produced process. Delivery becomes an interface for participation, intelligence, and orchestration, allowing firms to serve users not just as customers, but as collaborators in real-time energy ecosystems.

5.2.3 Digital Technologies and Value Capture

Value capture refers to how firms generate revenue from their offerings. In digitalized renewable energy models, traditional product-based income streams are increasingly replaced or complemented by service-based, data-driven, and decentralized monetization mechanisms. Three core patterns were identified:

1. Shift to service-based and recurring revenue models,
2. Personalized, data-driven pricing, and
3. Decentralized and participatory financial flows.

Insights from Interviews:

Case firms demonstrated varied approaches depending on their business model maturity. Firm D shifted from hardware sales to a SaaS subscription model, monetizing its simulation platform. Firm E’s PAYGO model enables micro-payments via mobile apps, aligning revenue with usage in low-income, off-grid markets.

Firm C offered the most sophisticated model, capturing value through real-time data APIs, tokenized investor payouts, and blockchain-enabled P2P energy trading. Firm A’s portfolio companies used AI to implement dynamic pricing and shared-savings mechanisms, adapting tariffs to demand patterns and performance.

These examples show how digital technologies enable firms to link revenue generation directly to system behaviour, customer usage, and financial inclusion.

Insights from the SLR:

The literature reinforces this shift toward flexible, digital-first monetization. Blockchain and smart contracts automate billing, support P2P exchanges, and enable tokenized ownership and revenue sharing (Mika et al., 2021; Gitelman & Kozhevnikov, 2023).

Energy-as-a-Service (EaaS) and SaaS models are widely discussed as emerging value capture architectures, shifting monetization from product sales to performance and platform use (Sulek et al., 2024; Pakulska & Poniatowska-Jaksch, 2022). AI and ML personalize tariffs and bundle services based on behavioural data (Vom Scheidt & Staudt, 2024; Bartczak, 2021).

PAYGO models in emerging markets align payment cycles with user cash flows and reduce credit risk (Rasagam & Zhu, 2018). Cooperative digital platforms enable prosumers to co-own infrastructure and participate in revenue distribution (Cooperative Digital Platforms, 2023).

Synthesis and Cross-Case Themes:

Both datasets suggest that value capture in digitalized renewable energy firms is shifting away from static, product-based pricing models toward dynamic, participatory, and service-oriented monetization. Recurring subscription models, personalized pricing, and tokenized flows are enabling firms to align financial value with usage patterns, system behaviour, and community participation.

Viewed through the lens of technology groupings, this transformation is driven by three key clusters:

- Group 4: Customer Interface and Engagement Platforms underpins flexible monetization by enabling PAYGO models, app-based billing, and real-time payment integration, shaping how customers interact with pricing and service tiers.
- Group 2: Data Processing and System Intelligence supports AI-driven personalization and performance-based pricing by tracking user behaviour, forecasting usage, and enabling segmentation strategies.
- Group 3: Trust and Coordination Infrastructure introduces decentralized and programmable revenue mechanisms, including blockchain-enabled peer-to-peer payments, tokenized ownership, and automated reward distribution.

Together, these technologies reconfigure value capture as a layered, data-responsive system, where pricing, billing, and value sharing are aligned with real-time behaviour and multi-actor participation. In doing so, they redefine financial logic from static product monetization to platform-mediated, trust-based economic flows.

Technology Group	Key Technologies	Primary BM Components Affected (as observed in this study)
Group 1: Data Capture and Embedded Infrastructure	IoT sensors, smart meters, edge devices, embedded chips, cyber-physical systems	Value Creation
Group 2: Data Processing and System Intelligence	AI, ML, big data, digital twins, swarm intelligence	Value Creation, Value Delivery, Value Capture
Group 3: Trust and Coordination Infrastructure	Blockchain, smart contracts, tokenization tools	Value Capture, Value Delivery
Group 4: Customer Interface and Engagement Platforms	Mobile apps, APIs, CRM platforms, cloud dashboards	Value Delivery, Value Capture
Group 5: System-Level Orchestration and Simulation	EMS, VPPs, planning tools, digital twins (for grid), cooperative platforms	Value Delivery, Value Creation

Figure 11. Mapping of Technology Groups to Business Model Components (based on findings from interviews and literature)

Interpretive Summary:

Based on the findings of this study, each technology group plays a distinct role in shaping business model components, though overlap and interdependence are common. Group 1 technologies support value creation by enabling system visibility and control, and often act as the foundational layer for other groups. Group 2 technologies embed intelligence into operational and pricing logic, influencing multiple components. Group 3 enables trusted, decentralized value exchange through programmable infrastructure. Group 4 redefines customer interaction and service access, while Group 5 facilitates distributed coordination and system-level orchestration.

These roles are drawn from patterns observed in our interviews and literature analysis. However, the same technologies may serve different purposes in other contexts or affect additional business model components depending on how they are integrated and applied. The interplay between groups underscores that business model change is typically triggered by layered, mutually reinforcing digital functions, not single-point solutions.

5.3 Interpreting Business Model Change: BMA, BME, or BMI?

To address the third sub-question of this thesis:
How do business models evolve over time in response to digitalization in high-tech renewable energy firms?

5.3.1 Interpretive Logic for Business Model Change

To classify the type of business model change observed in each firm, this study applies three interpretive criteria drawn from the academic literature: degree of change, structural impact, and introduction of new logic. These criteria collectively help distinguish between Business Model Adaptation (BMA), Business Model Evolution (BME), and Business Model Innovation (BMI). Rather than treating these categories as mutually exclusive, the framework views them as points along a spectrum of transformation. The aim is to interpret the type of change in each case, based on the nature and role of digital technologies in shaping business model components. This framework is applied consistently to both the interview-based firm cases and the literature-based SLR cases presented in the following sections, enabling comparative interpretation of business model transformation across empirical and theoretical contexts.

1. **Degree of Change** – This criterion refers to the overall magnitude of transformation. Business model adaptation is typically characterized by small, context-specific adjustments that respond to external constraints or temporary needs (Saebi et al., 2017; Balboni & Bortoluzzi, 2015). Evolution, by contrast, reflects an ongoing and internally driven process of improvement, often emerging through learning-by-doing, feedback loops, and the gradual refinement of activities (Demil & Lecocq, 2010; Khodaei & Ortt, 2019). Innovation denotes a more profound shift, marked by the deliberate pursuit of novelty and strategic repositioning (Foss & Saebi, 2017). Prior literature emphasizes that while BMA is reactive and localized, BME is progressive and cumulative, and BMI reflects a more radical rethinking of the firm's business model trajectory (Saebi, 2014; Foss & Saebi, 2017; Demil & Lecocq, 2010).
2. **Structural Impact** - This criterion assesses the extent to which digitalization affects the core components of the business model, namely, value creation, value delivery, and value capture. Adaptation usually involves isolated changes to one component, such as adjusting a pricing model or delivery mechanism in response to market conditions. Evolution tends to involve multiple components being modified usually in an interrelated way, while still preserving the firm's overall value logic (Demil & Lecocq, 2010; Khodaei & Ortt, 2019). Innovation, on the other hand, is associated with more substantial reconfigurations that challenge existing structures and introduce novel mechanisms or relationships. (Teece, 2010; Foss & Saebi, 2017). Structural impact thus helps distinguish between fine-tuning existing systems and reorienting the model in response to new technological or market opportunities.
3. **Introduction of New Logic** - The final criterion considers whether the change introduces a fundamentally new way of creating, delivering, or capturing value. This includes shifts such as transitioning from product-based to service-based delivery, adopting platform-based ecosystems, enabling tokenized revenue flows, or reimagining customer roles. The emergence of a new value logic indicates that digital technologies are not merely enhancing operations but are acting as enablers of strategic transformation. As noted by Chesbrough (2010), Zott et al. (2011), and Massa & Tucci (2013), such changes often redefine how the firm interacts with its ecosystem and how it captures value from its activities. In these cases, digitalization becomes a driver of strategic reconfiguration, where the business model is restructured around a new set of guiding principles.

These criteria are applied together, not in isolation. For example, a firm may demonstrate strong structural impact but retain its original logic, aligning more closely with BME than BMI. Similarly, changes affecting multiple components are not necessarily innovative unless they involve a clear break from past logic. In this study, the classification is based on interpretive synthesis rather than rigid scoring, allowing for nuance while ensuring consistency in how each firm is evaluated. Where multiple change types coexist (e.g., an innovative shift followed by incremental refinements), these are interpreted using the concept of Business Model Dynamics (BMD), which captures the layered and temporal nature of digital transformation.

5.3.2 Firm-Level Interpretation from Interviews

The following case-wise interpretations synthesize empirical insights from interviews using the criteria introduced above.

Firm A
A venture capital firm investing in early-stage energy tech startups, does not operate a business model of its own in the traditional sense. However, the insights it offers into its portfolio companies provide a useful window into the types of digital transformations unfolding across the sector. According to the interview data, many of these startups have adopted technologies such as artificial intelligence (AI) and Internet of Things (IoT) to enhance forecasting, automate electricity procurement, and improve energy system efficiency. These digital tools support changes in value creation and delivery, such as the development of predictive analytics tools and white-labelled SaaS dashboards for utility clients.

Applying the interpretive criteria introduced in Section 5.3.1, the degree of change observed in these startups appears to be incremental to moderate, reflecting performance-driven improvements rather than radical reconfigurations. The structural impact spans at least two components-value creation and delivery-but tends to reinforce existing models rather than replace them. Notably, there is no clear introduction of a new value logic; monetization mechanisms and client relationships remain largely conventional. As noted by Firm E, “It’s very difficult for startups to radically innovate when they’re tied into utility infrastructure , that’s a very conservative system, so what you mostly see is incremental change.” This ecosystem-level constraint helps explain why the startups observed by Firm A remain within evolutionary trajectories despite their technological maturity.

Taken together, these characteristics are most consistent with Business Model Evolution (BME). The startups in question are actively leveraging digital technologies to scale and optimize their offerings, but the changes remain cumulative, learning-driven, and aligned with their existing strategic configurations.

Firm B
Firm B is a high-tech solar firm focused on circularity and sustainable hardware design. It has embedded Internet of Things (IoT) sensors into its photovoltaic modules and partnered with a blockchain platform provider to implement traceability across the product lifecycle. These digital technologies allow the firm to monitor system performance, collect data for maintenance and recovery, and provide transparency about the material origin and usage of its panels. While these capabilities strengthen Firm B’s value proposition and contribute to long-term sustainability goals, they do not yet reflect a radical reconfiguration of the firm’s business model.

Applying the interpretive criteria, the degree of change observed at Firm B is incremental to moderate. The integration of IoT and blockchain technologies improves operational capabilities and stakeholder transparency, but these enhancements serve to reinforce the firm’s existing sustainability logic rather than establish a new one. The structural impact is visible primarily in value creation and, to some extent, value delivery, particularly through the traceability layer and product lifecycle services. However, the underlying monetization mechanisms and customer relationships remain unchanged, and there is no indication of a new value logic or platform-based service emerging at this stage.

Notably, the interview also revealed future ambitions to enable resale and second-life business models through blockchain-based ownership tracking. While these ideas may eventually lead to business model innovation, they remain unrealized and therefore fall outside the scope of this classification. As such, Firm B is best understood as engaging in Business Model Evolution (BME), where digital technologies are actively used to optimize and extend an existing sustainability-oriented model, without fundamentally altering its structure or logic.

Firm C

Firm C, a technology-driven solar company, entered the market with a digital-first, platform-oriented business model that fundamentally departs from traditional solar deployment logic. Its model is anchored in a proprietary IoT-enabled sensor embedded in solar infrastructure, enabling real-time monitoring, authenticated data streams, and predictive analytics. However, the core innovation lies not in the sensor itself, but in the digital ecosystem built around it, one that transforms data into a monetizable asset and orchestrates interactions across a wide range of energy market stakeholders.

From inception, the firm positioned itself as a platform orchestrator, leveraging digital infrastructure to monetize verified energy data and facilitate new value streams. Blockchain is used to certify asset origin, manage digital identities for solar components, and enable peer-to-peer (P2P) energy trading. It also supports programmable energy use, tokenization of solar infrastructure, and platform governance for local energy communities. Financial mechanisms include green bond issuance and fractional asset ownership based on operational data, while IoT-driven analytics support insurance modelling. As the interviewee summarized, “We don’t just sell panels; we build a data economy around them.” These mechanisms span all business model components: value creation through embedded, authenticated data streams; value delivery via APIs, dashboards, and stakeholder integration; and value capture through tokenization, green finance, insurance data services, and carbon market participation. This transformation was enabled by a multi-layered digital stack combining technologies from Group 1 (IoT-enabled data capture), Group 2 (AI-driven analytics and system intelligence), and Group 3 (blockchain-based identity and transaction coordination), which collectively reconfigured the firm’s value creation, delivery, and capture mechanisms.

According to the interpretive criteria, Firm C exhibits a high degree of change, a comprehensive structural reconfiguration, and a distinctly new value logic. It does not merely optimize solar operations; it transforms them into digital assets with programmable and financial utility. As interviewee noted, “The value is not just in the solar panels, but in how the data flows from them into actionable insights, our dashboard helps owners and operators make better decisions, optimize usage, and even plan financial models.”

Beyond its foundational business model innovation, the firm continues to evolve through ongoing business model evolution (BME). It uses artificial intelligence to detect technical anomalies and improve product design. The firm has also refined its system interfaces over time to unify the user experience across installers, asset owners, and operational dashboards. These refinements reflect a continuous learning process that enhances operational performance and platform usability.

Taken together, Firm C reflects clear Business Model Dynamics (BMD). It combines a digitally native, platform-based business model (BMI) with iterative, learning-driven improvements

(BME), illustrating how firms at the innovation frontier continue to evolve their models even after radical transformation.

Firm D

Firm D presents a layered case of business model change, combining a foundational strategic pivot with ongoing incremental improvements. The company originally operated as an energy management systems (EMS) provider, offering hardware-software combinations for on-site performance optimization. However, as the founder explained, “It was mostly hardware-based in the beginning, yes. And that was very difficult to scale. And so, now it’s completely cloud-based. We have a software tool that you can use without installing anything. You just log in and start simulating.” This transition marked a significant reconfiguration of the firm’s value creation, delivery, and capture mechanisms. This shift was supported by technologies from Group 2 (cloud-based simulation and AI-enhanced decision tools), Group 4 (SaaS delivery interfaces), and Group 5 (system-level orchestration using digital twins and external data streams), which together enabled the firm to digitize, modularize, and scale its business model.

Applying the interpretive criteria, this pivot constitutes a clear case of Business Model Innovation (BMI). The firm moved from delivering optimization services through hardware-dependent systems to offering a digital twin–based simulation platform. Value creation shifted to automated, cloud-based design capabilities. Value delivery was restructured through a self-service SaaS interface that allows EPCs to run real-time simulations and access external data streams such as Google Maps and weather APIs. Value capture also evolved, with a transition from project-based revenue to subscription pricing. Most importantly, the firm adopted a new value logic: rather than designing systems for clients, it now enables clients to simulate and optimize systems independently.

Since establishing its simulation platform, Firm D has continued to refine and improve its offering through iterative, learning-driven adjustments. These include embedding AI into internal development processes to accelerate tool design and extend simulation capabilities. These improvements reflect Business Model Evolution (BME), ongoing refinements to the firm’s digital infrastructure and service performance without altering its underlying value logic.

Taken together, Firm D exemplifies Business Model Dynamics (BMD). Its history includes both a strategic reconfiguration (BMI) and continued incremental innovation (BME), illustrating how business models may evolve through multiple, overlapping change trajectories. Rather than experiencing a single shift, Firm D’s transformation has unfolded through a layered sequence of innovation and refinement, each shaped by digital technologies and organizational learning.

Firm E

Firm E, a solar energy firm operating in underserved and off-grid markets, illustrates a dynamic and layered pathway of business model change. The company initially launched with a centralized kiosk model for energy access, relying on local agents and physical infrastructure. However, this model proved difficult to scale. As the interviewee explained, “We started off with the concept… a centralized kiosk system… But we finally figured out this is not scalable. And then we moved into this pay-as-you-go system… and that has massively scaled up.” This shift to a mobile-enabled PAYG system, supported by IoT-enabled hardware, mobile apps, and cloud-based monitoring, represents a radical redesign of the firm’s value delivery and capture logic, consistent with Business Model Innovation (BMI). The change was driven by the deployment of technologies from Group 1 (IoT-enabled hardware), Group 2 (AI for onboarding and credit scoring), and Group 4 (mobile applications and cloud dashboards), which enabled a user-centric, flexible, and scalable service model tailored to off-grid conditions.

The new model allows customers to purchase energy in micro-units via mobile payments and manage their systems remotely. Value delivery is now entirely digital, and value capture is embedded into the daily usage experience. This transformation goes beyond operational change, it reflects a new business logic centred on flexibility, autonomy, and low-friction access to clean energy.

Following this pivot, the firm has continued to evolve through incremental digital enhancements. AI is being developed to automate credit scoring and personalize onboarding for new users, mobile apps are used to manage accounts, track usage, and troubleshoot technical issues. These reflect Business Model Evolution (BME), ongoing improvements to digital infrastructure, user experience, and internal processes without altering the core value logic of the business.

In addition, Firm E demonstrates context-driven Business Model Adaptation (BMA). In areas with poor network connectivity, the firm built local caching to ensure system functionality: “In some regions, mobile networks are weak… we’ve had to adapt by building local caching so the system works offline and syncs later.” These adjustments reflect tactical, environment-specific adaptations that improve feasibility without strategic reconfiguration.

Taken together, Firm E exemplifies Business Model Dynamics (BMD), where different forms of business model change coexist and evolve over time. The firm’s trajectory includes a foundational innovation (BMI), continuous refinement (BME), and localized adaptations (BMA), illustrating how digitalization can drive both strategic reinvention and operational resilience in emerging-market contexts.

Conclusion

Taken together, the firm-level classifications in this section illustrate that business model change in the renewable energy sector occurs along a spectrum, from incremental adaptations to structural innovation. By applying literature-derived interpretive criteria related to degree of change, structural impact, and new logic, this study was able to differentiate between Business Model Adaptation (BMA), Business Model Evolution (BME), and Business Model Innovation (BMI). Importantly, these categories were not always discrete. In several cases, such as Firms C, D, and E, multiple types of change were observed simultaneously or sequentially. Across cases, the type and extent of business model change were shaped not only by the adoption of digital technologies, but by how strategically firms combined multiple technology groups, particularly Groups 1 through 4, to embed capabilities across creation, delivery, and capture. Firms classified under BMI typically deployed layered stacks that spanned infrastructure, intelligence, interface, and trust functions. This reinforces the idea that business models are not static configurations but evolving systems, laying the groundwork for the next section, which explores cross-case patterns and introduces integration depth and Business Model Dynamics (BMD) as interpretive lenses.

Table 6. Business Model Change Classification by Firm

Firm	Degree of Change	Structural Impact	New Value Logic	Primary Change Type	Additional Types	BMD Observed
B	Incremental	1–2 components	No	BME	–	No
C	High	All components	Yes	BMI	BME	Yes
D	High	All components	Yes	BMI	BME	Yes
E	High	All components	Yes	BMI	BME + BMA	Yes

5.3.3 Business Model Change Patterns in the SLR

This section draws on the systematic literature review (SLR) to assess how academic studies interpret and classify business model change in digitally enabled renewable energy systems. The aim is to complement the interview-based firm-level classifications in Section 5.3.2 with broader theoretical and empirical patterns observed across the academic literature.

Business Model Adaptation (BMA) appears frequently in contexts where digital technologies are used to improve internal operations, ensure regulatory compliance, or support sustainability goals, without altering the core business model logic. Examples include the implementation of substation automation to improve fault detection (Leiva Vilaplana et al., 2025), or the use of AI tools for scenario planning aligned with SDGs (Franki et al., 2023). These applications serve as tactical enhancements or reporting mechanisms, often embedded within existing workflows and infrastructures. The changes are localized, technically meaningful, but strategically bounded, reflecting adaptation to policy, customer, or environmental pressures without deep structural change.

Business Model Evolution (BME) is reflected in studies where digital technologies enable operational restructuring, multi-component integration, or enhanced service coordination, while still preserving the underlying business logic. Digital twins, smart meters, and AI forecasting systems are commonly used to improve grid responsiveness, predictive maintenance, and system efficiency (Adnan et al., 2024; Skaloumpakas et al., 2024). These tools allow firms to evolve toward more flexible and intelligent energy systems, often by integrating new decision-making capabilities or delivery mechanisms. However, the core offerings, revenue models, and actor roles largely remain intact. The transformation is thus cumulative, system-level, and infrastructure-focused, hallmarks of BME.

Business Model Innovation (BMI) is identified in papers that describe more radical transitions, particularly those involving platformization, tokenization, or new value logics. Examples include mobile-enabled Pay-As-You-Go (PAYG) models that shift value capture from ownership to access (Rasagam & Zhu, 2018), peer-to-peer (P2P) trading platforms enabled by blockchain (Mika et al., 2021), and tokenized solar investment ecosystems that redefine asset ownership and monetization (Neska & Kowalska-Pyzalska, 2022). These studies highlight how digital technologies not only restructure delivery and pricing models, but also introduce new roles for users (e.g., prosumers, co-investors) and redistribute control through decentralized architectures. In such cases, the firm's role is reimagined, from service provider to ecosystem orchestrator, marking a clear departure from traditional energy business models.

Across all three types of change, the literature also reflects a growing emphasis on layered technology integration, where multiple digital tools, such as AI, IoT, blockchain, and digital twins, interact in shared architectures. This convergence often supports hybrid or dynamic business models that combine evolutionary efficiency with innovative features. Such examples point to Business Model Dynamics (BMD), an emerging conceptual lens where adaptation, evolution, and innovation coexist over time or across components. While BMD is not always explicitly labelled in the literature, several studies imply layered transitions that mirror the multi-trajectory patterns observed in the interview cases (e.g., Singh et al., 2021; Bartczak, 2021; Gitelman & Kozhevnikov, 2023).

The SLR confirms that digital technologies can drive all three types of business model change. The type of change depends less on the technology itself than on its configuration, purpose, and institutional context. These findings align closely with the firm-level patterns in this study and reinforce the need for a dynamic, spectrum-based interpretation of business model transformation in the renewable energy sector.

Notably, several papers in the SLR also implicitly reflect the role of functional technology groups, such as sensing (Group 1), intelligence (Group 2), and coordination infrastructure (Group 3), in shaping business model change. For instance, platform-based innovation is often enabled through layered integration of data capture, predictive analytics, and decentralized transaction tools. While most studies do not explicitly categorize digital tools in functional groupings, the underlying patterns mirror the empirical classifications observed across the interview cases. This reinforces the idea that business model transformation in renewable energy is frequently driven by cumulative, interoperable stacks of technologies that interact across creation, delivery, and capture functions.

5.4 Cross-Case Patterns and the Role of Integration Depth (Based on Interviews)

The previous section offered firm-level classifications of business model change based on the interpretive criteria of degree of change, structural impact, and introduction of new value logic. This section shifts focus to a comparative perspective, identifying broader patterns that emerge across the five interview cases. It examines how different types of business model change - adaptation, evolution, and innovation - are shaped not only by the nature of digital technologies adopted, but also by contextual factors such as market positioning, organizational maturity, and the depth of digital integration.

In doing so, this section introduces a key empirical observation from the study - the observed relationship between the extent of digital integration within a firm's architecture and the type of business model transformation it undergoes. Rather than treating change as a binary or linear outcome, this perspective aligns with the concept of Business Model Dynamics (BMD), which views transformation as a layered, iterative, and context-sensitive process.

5.4.1 Cross-Case Comparison and Variation

A comparison of the five case firms reveals significant variation in the nature, scope, and sequencing of business model change. Rather than following a uniform trajectory, firms respond to digitalization in diverse ways, shaped by their founding logic, technological capabilities, and operating environments.

Some firms, such as those in Firm A's investment portfolio, demonstrate incremental improvements through digital tools like AI and IoT, while largely retaining their original value logic and monetization models. This aligns with Business Model Evolution (BME). Other firms, like Firm C, entered the market with entirely new, platform-based models and exhibit clear characteristics of Business Model Innovation (BMI), yet continue to evolve incrementally over time through enhancements in AI, user interfaces, and service orchestration. Similarly, Firms D and E experienced strategic pivots that reflect BMI but have continued to refine their models through ongoing improvements consistent with BME.

This study finds that multiple types of business model change can and often do coexist within a single firm. In particular, BME is frequently observed even after a BMI event, demonstrating that innovation often marks the beginning of an iterative cycle of learning and optimization rather than an endpoint. Conversely, in resource-constrained or infrastructure-dependent environments, Firms B and E exhibit localized adaptations (BMA) in parallel with broader evolutionary or innovative changes.

Additionally, contextual enablers and constraints influence which type of business model change is feasible or pursued. For instance, Firm B's blockchain-enabled traceability enhances its sustainability goals but does not currently reshape its revenue or delivery logic. In Firm E, weak mobile connectivity in rural markets prompted tactical adaptations, such as offline data caching, which align with BMA.

These observations support the view that business model change is not a singular, linear transition but a dynamic and overlapping process. This aligns with the concept of Business Model Dynamics (BMD), the idea that firms experience sequential, parallel, or layered changes across business model components, shaped by both internal learning and external constraints.

5.4.2 Digital Integration Depth as an Explanatory Lens

To support a deeper interpretation of business model change across the firms studied, this section introduces the concept of digital integration depth. While prior literature has examined the influence of specific digital technologies on firms, it does not provide a systematic lens to assess how broadly and centrally these technologies are embedded within a firm's value architecture.

This study proposes integration depth as an analytical dimension to describe the extent to which digital technologies are woven into value creation, delivery, and capture. Crucially, depth refers not just to the number of tools adopted, but to how significantly these tools shape or redefine the business model structure and logic.

Based on empirical findings, three levels of integration depth are defined:

- High Integration: Digital technologies form the foundation of the business model, deeply embedded across value creation, delivery, and capture.

- Moderate-to-High Integration: Digital tools are essential to scaling or service delivery but the core business logic remains only partially digital.
- Moderate Integration: Technologies support traceability, efficiency, or monitoring, but without reconfiguring the business model architecture.

Firm C exemplifies high integration, with a platform architecture embedding IoT, blockchain, and APIs across all components. These technologies not only support operations, they define the firm's monetization logic and sectoral role.

Firm D and Firm E exhibit moderate-to-high integration. Firm D's digital twin simulation platform forms the core of its proposition but remains scoped to a specialized segment (EPCs). Firm E relies on mobile apps, AI, and PAYG infrastructure to transform delivery and capture, though its value logic remains focused on energy access rather than digital service monetization.

Firm B demonstrates moderate integration, using IoT and blockchain to support operational transparency, but not to restructure revenue streams or delivery logic.

Firm A, as a venture investor, does not operate a business model of its own and is excluded from this classification.

This variation in integration depth helps explain the types of business model change observed. Firm C, with deep integration, demonstrates sector-level BMI. Firms D and E, with targeted but transformative digital architectures, also achieve BMI within firm boundaries. Firm B, by contrast, evolves its model incrementally through efficiency gains without introducing new value logic, corresponding to BME.

Importantly, BMA is shaped less by integration depth and more by environmental conditions or other constraints, such as connectivity constraints, as seen in Firm E's offline data caching. Additionally, BME appears across all cases, often as a continuing layer of refinement even after BMI or BMA events.

Overall, integration depth emerges as a valuable interpretive lens. It does not deterministically predict business model change, but it helps clarify how digital technologies contribute to transformation, and to what extent they redefine business logic. This reinforces the view of Business Model Dynamics (BMD) as a layered, context-sensitive, and evolving phenomenon.

Table 7. Cross-Case Summary of Integration Depth and Business Model Change Types

Firm	Integration Depth	BMI Present	BME Present	BMA Present	Notes on Change Trajectory
Firm A	Observer only	✗	✓ *(via portfolio firms)*	✗	Observes incremental BME in startups (e.g., AI, IoT)
Firm B	Moderate	✗	✓	✗	Operational improvements via IoT and blockchain; ESG-driven but no structural shift
Firm C	High (Full-stack)	✓	✓	✗	Platform-based logic from start (BMI); continues evolving interfaces, partnerships, operations and analytics (BME)
Firm D	Moderate-to-High	✓	✓	✗	Pivot to SaaS (BMI); ongoing enhancements using AI and interface refinements (BME)
Firm E	Moderate-to-High	✓	✓	✓	PAYGO model restructured delivery and capture (BMI); AI onboarding and app refinement (BME); offline caching for rural constraints (BMA)

5.5 Cross-Cutting Reflections and Key Observations

While the preceding sections have examined business model change from firm-level and technology-integration perspectives, this section presents a synthesis of broader patterns and conceptual insights that emerged across both the interview and literature datasets. These cross-cutting reflections do not aim to restate earlier findings, but rather to highlight key meta-level observations that offer strategic and theoretical implications.

1. **Temporal Distribution and Recency of Literature**

A clear pattern observed in the SLR is the recency of academic contributions: the vast majority of included studies were published between 2021 and 2024. This temporal clustering reflects the growing scholarly interest in how digitalization intersects with renewable energy business models. At the same time, it highlights the emergent and still-maturing state of this research domain. Many papers remain exploratory or conceptual, with limited empirical validation, reinforcing the importance of this thesis in providing grounded case-based insights to complement and extend the evolving academic discourse.

2. **Layered Technology Stacks, Not Isolated Tools**

Both empirical and literature data underscore that digital technologies are rarely applied in isolation. Instead, firms typically employ layered technology stacks, for example, combining IoT with cloud dashboards, or AI with digital twins and simulation tools. These combinations are essential for enabling responsiveness, automation, and multi-actor coordination. This observation challenges overly reductionist frameworks that assess technologies individually rather than systemically.

3. **Multi-Functional and Cross-Component Influence**

A single digital technology often serves multiple purposes and affects multiple business model components simultaneously. For instance, blockchain may enable both traceability (value delivery) and new monetization models (value capture), while IoT supports both operational optimization (value creation) and personalized service delivery (value delivery). This highlights the need to analyze technology influence holistically, rather than through siloed BM component lenses.

4. **Context Dependency and Non-Linearity**

The effect of a given technology on business model change is highly context-dependent. The same digital tool may enable Business Model Innovation (BMI) in one firm but only support Evolution (BME) in another, depending on factors such as infrastructure readiness, customer base, firm maturity, and regulatory environment. This non-linearity reinforces the relevance of Business Model Dynamics (BMD) as a more realistic interpretive frame.

5. **Pervasiveness of AI and Blockchain**

Artificial Intelligence (AI) and Blockchain emerged as the most broadly applicable and cross-component technologies across both datasets. AI is leveraged for forecasting, personalization, and simulation, while blockchain supports trust infrastructure, peer-to-peer trading, and tokenized ownership. Their versatility and integration potential make them key enablers of digital transformation in renewable energy.

6. **IoT as a Foundational Technology Layer**

IoT consistently appears as the foundational layer in digital architectures. Since digital transformation relies on real-time, high-resolution data, the ability of IoT to convert physical system signals into actionable digital inputs underpins almost every other application, be it in AI analytics, digital twins, or dynamic pricing models. Its role as an enabler rather than a standalone value creator is crucial for understanding digital system architecture.

7. **Business Model Change Not Solely Technology-Driven**

Crucially, the study finds that the type of business model change (BMA, BME, BMI) is not solely determined by the digital technology adopted. Instead, it depends on how the technology is applied, whether it is layered into a core service, used peripherally for reporting or traceability, or leveraged to create entirely new value structures. This supports prior literature emphasizing that business model innovation is as much about strategic framing and organizational context as it is about technical capability.

Conclusion

The conceptual model presented in Chapter 2 remains broadly validated by the findings of this study. However, the empirical insights allow us to refine its structure and interpretation. First, digital technologies do not operate as isolated tools, but as interdependent functional clusters that enable sensing, coordination, and engagement across the business model. Second, business model changes occur not as discrete events but as layered and recursive processes, where innovation may trigger continued refinement (BME) and contextual adaptation (BMA) in parallel. Third, the introduction of digital integration depth offers a critical explanatory lens, clarifying not just the presence of digital tools but the extent to which they redefine value creation, delivery, and capture.

Moreover, the revised model distinguishes between tactical, iterative, and strategic change pathways, and clarifies that while BME and BMI are closely linked to integration depth, BMA is more strongly driven by contextual constraints. These refinements offer a more nuanced and dynamic view of Business Model Dynamics (BMD) in digitalized renewable energy contexts.

A revised version of the model, reflecting these findings, is presented below.

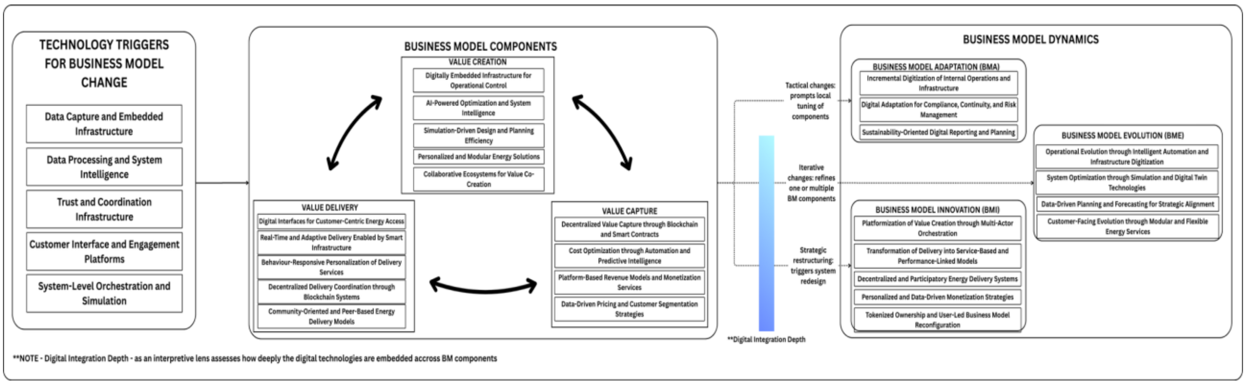

Figure 12. Refined Conceptual Model: Updated Post Empirical and Literature-Based Analysis

5.6 Interview-Based Insights on Limitations of Digital Infrastructures

While digital technologies are central to the transformation of business models in the renewable energy sector, interview participants emphasized that existing digital systems are not without significant shortcomings. This section synthesizes insights regarding the architectural, operational, and security-related vulnerabilities that currently affect digital infrastructures in this domain.

A prominent critique came from Firm C, which highlighted the lack of transparency, auditability, and distributed control in legacy smart meter architectures. These systems often function under centralized ownership, typically by a single vendor or government agency, creating dependencies, limiting interoperability, and posing risks for multi-actor ecosystems like carbon credit verification or peer-to-peer energy trading.

> *"Right now you have a smart meter company and it becomes the key master of all the data... They're not modern cryptography or IoT enabled. The smart meter feeds are not trusted... There's no distributed source of truth... That's the problem in the industry." (Firm C)*

These issues reflect two foundational limitations:

- Centralized control and lack of independence: Single-entity control over energy data creates bottlenecks and reduces systemic trust.
- Absence of cryptographic safeguards: Many systems lack verifiability, tamper resistance, or secure validation layers, making them vulnerable to manipulation.

To respond to these limitations, some firms are actively re-architecting their systems using blockchain and distributed ledger technologies. For instance, both Firm B and Firm C incorporate blockchain-based mechanisms to enable traceability, data integrity, and third-party verifiability, particularly in applications like product passports, carbon credit validation, and yield tracking. By distributing control and ensuring immutability, blockchain helps overcome one of the core vulnerabilities of centralized systems: the lack of a shared, tamper-proof source of truth.
Firm C also raised concerns about cybersecurity, particularly the threat of digital manipulation or intrusion into sensitive renewable energy assets. In response, the firm integrates dedicated cybersecurity layers within its platform to safeguard against data breaches, sensor spoofing, or external interference. This recognition points to a new layer of risk introduced by digitization, especially as firms move toward real-time, automated systems.

> *"The industry really needs to be extremely protective of the asset… There's a whole cybersecurity layer that we offer to the industry." (Firm C)*

In addition to architectural and security issues, operational limitations were identified by Firm E, which works in remote, infrastructure-limited energy markets. In some regions, poor connectivity and unreliable mobile networks create friction in executing digital operations, such as remote diagnostics, real-time payments, or IoT-based monitoring.

> *"Connectivity is a big issue in some areas… it affects our ability to do real-time diagnostics or track usage data reliably." (Firm E)*

These insights reveal that digital transformation is not only about technology adoption but also about infrastructure readiness and systemic robustness. As digital business models scale into new geographies or across value chains, firms must navigate the interplay between technological potential and infrastructural constraints, adapting architectures for resilience, security, and trust.

5.7 SLR-Based Insights on Limitations of Digital Infrastructures

While digital technologies offer transformative potential for renewable energy systems and business model innovation, their integration into the energy sector is fraught with limitations. This section synthesizes findings from the systematic literature review to outline the multifaceted barriers that hinder effective implementation. These limitations span six key domains: data-related, technological, economic, organizational, regulatory, and socio-ethical concerns.

Data-Related Challenges

A recurring concern across the literature is the quality, availability, and security of data that underpin digital energy systems (Ahmad et al., 2021; Franki et al., 2023 ; Adnan et al. ,2024; Neska and Kowalska-Pyzalska, 2022; Pakulska and Poniatowska-Jaksch, 2022) . Poor data quality, stemming from low-fidelity sensors, faulty controllers, and incomplete information, compromises the reliability of AI-driven applications. The high dimensionality of energy datasets, especially in large-scale simulations, adds layers of complexity to system modelling and predictive analysis. Furthermore, overlapping datasets and climate-driven unpredictability complicate real-time decision-making processes. (Liu et al., 2022; D'Amore et al. ,2022; Franki et al., 2023 ; Adnan et al. ,2024;)

Data privacy and cybersecurity risks are particularly pronounced in systems reliant on IoT devices and decentralized infrastructures (Bartczak , 2021 ; Bartczak and Łobejko , 2022 ; Mika and Goudz, 2021 ; Venkatachary et al., 2017; Gitelman and Kozhevnikov, 2023) . IoT-based metering and monitoring systems often lack robust encryption due to hardware constraints, exposing sensitive consumer data to potential breaches. Additionally, the immutability of blockchain, while beneficial for transparency (Skaloumpakas et al., 2024; Augello et al., 2022; Liu et al., 2022), conflicts with privacy regulations such as the right to erasure, raising compliance concerns(Mika and Goudz, 2021). These unresolved issues reflect the sector's need for more secure, interoperable, and privacy-compliant data architectures.

Technological Constraints

The technological limitations of digital energy systems are both fundamental and operational (Ciano et al., 2025; Ahmad et al., 2021; Mika and Goudz, 2021). Integration with existing infrastructure remains a critical hurdle, particularly for legacy systems unprepared for the complexities introduced by AI, blockchain, or IoT. AI systems, for instance, demand high computational capacity and require precise tuning of hyperparameters, making deployment resource-intensive and technically demanding (Ahmad et al., 2021; Franki et al., 2023). Moreover, AI's "black box" nature and its inability to process unstructured or incomplete data can reduce system transparency and user trust. (Ahmad et al., 2021)

IoT devices face decentralization and interoperability issues, while blockchain suffers from scalability and transaction speed constraints, particularly when operating under proof-of-work mechanisms(Mika and Goudz, 2021). The integration of smart meters with blockchain systems is also hindered by incompatible communication gateways, necessitating technological workarounds. As digitalization progresses, these constraints are exacerbated by the obsolescence of existing infrastructure, the lack of standardized software protocols, and the increasing complexity of automation and control systems(Franki et al., 2023; Liu et al., 2022; Mika and Goudz, 2021).

Economic and Financial Barriers

Deploying digital technologies in renewable energy systems entails significant capital and operational expenditure. High upfront costs for software development, hardware acquisition, data storage, and skilled labour create economic disincentives, particularly for small and medium-sized enterprises(Ahmad et al., 2021). Even in larger firms, the cost-benefit ratio of certain technologies, such as blockchain, is questioned due to unclear returns on investment and excessive energy consumption.(Mika and Goudz, 2021)

This challenge is compounded by sectoral disparities (D'Amore et al., 2022). For example, some energy subdomains like wind storage or mini-grid operations lack digital investment attractiveness (Pakulska and Poniatowska-Jaksch, 2022) or struggle to recover costs through tariffs due to government-imposed price caps(Rasagam and Zhu, 2018). These asymmetries in cost-benefit realization highlight the need for more inclusive financial models and targeted policy incentives to support digital innovation.

Organizational and Managerial Challenges

Beyond technical and financial barriers, organizational readiness and managerial capability are pivotal for digital transformation(Malewska et al., 2024). Many firms face a shortage of skilled personnel, particularly in AI and data science, limiting their ability to design, operate, and scale digital tools(Ahmad et al., 2021). Moreover, existing workflows often require restructuring to accommodate digitally driven decision-making, necessitating significant upskilling and cultural adaptation(Del Vecchio et al., 2025).

Weak digital governance structures further hinder transformation. Unclear market roles, limited stakeholder coordination, and neglected business model frameworks reduce the strategic coherence of digital initiatives (Del Vecchio et al., 2025). In highly decentralized systems, coordination becomes critical to ensure grid stability and efficient service delivery. However, fragmented partnerships and interdependencies among platform actors introduce operational risks that require deliberate management strategies(D'Amore et al., 2022).

Regulatory and Policy Barriers

The regulatory landscape for digital technology integration remains underdeveloped and fragmented (Ahmad et al., 2021; Gitelman and Kozhevnikov, 2023; Hu et al., 2022; Malewska et al.,2024; Mika and Goudz, 2021). Legal uncertainties around blockchain, including the enforceability of smart contracts and jurisdictional conflicts, create adoption hesitancy. Moreover, legacy policy frameworks often fail to accommodate the decentralized, transnational, and automated nature of digital systems.(Mika and Goudz, 2021)

Standardization and interoperability challenges persist due to a lack of unified international reporting norms, especially for evaluating sustainability and cross-sector impacts (Mika and Goudz, 2021). Furthermore, planning procedures, entrenched stakeholder interests, and outdated regulations delay innovation and infrastructure upgrades (Hu et al., 2022). In the context of emerging business models such as peer-to-peer trading and virtual power plants, clear legal definitions and supportive policy frameworks are critical to enabling scalability (Mika and Goudz, 2021).

Social and Ethical Concerns

Digitalization also presents social and ethical dilemmas that are often underrepresented in technical assessments. The risk of social exclusion, termed "digital poverty", arises from unequal access to digital infrastructure, skills, and financial capital (D'Amore et al., 2022; Adnan et al.

,2024). Additionally, increased automation raises concerns about labor displacement, particularly among low-skilled workers, potentially exacerbating socio-economic inequalities.

Public skepticism around data surveillance, algorithmic decision-making, and perceived loss of autonomy may also slow adoption (D’Amore et al., 2022). Blockchain, while enhancing transparency, is susceptible to illegal activities and irreversible data loss due to the lack of central authority (Mika and Goudz, 2021). Moreover, the ecological impact of digital technologies themselves, such as the carbon footprint of AI training or blockchain mining, challenges their alignment with environmental goals and circular economy principles(D’Amore et al., 2022).

5.8 Synthesis: Comparing Interview-Based and Literature-Based Limitations

Both the interview data and the literature highlight important constraints in the integration of digital technologies within the renewable energy sector, but they focus on different aspects. The interviews provide grounded, practice-based insights, particularly around architectural and infrastructural issues such as centralized data ownership, limited system auditability, and, in some cases, vendor lock-in due to proprietary platforms. These concerns were not prompted by specific questions but emerged organically during broader conversations about digital strategies. Given the limited interview duration and the broader focus of the discussions, barriers were not explored systematically. As a result, the limitations identified likely reflect only the most immediate and visible challenges faced by practitioners.

The literature, by contrast, offers a more comprehensive and conceptual perspective. It covers a wide range of limitations, including issues related to data quality, regulatory fragmentation, technological scalability, and ethical concerns. While some overlap exists, for instance, both the interviews and literature mention cybersecurity risks, other themes diverge. Interviewees, for example, spoke about operational hurdles such as offline syncing or dependencies on specific vendors, which are less commonly discussed in academic sources. Conversely, literature contributions often explore more abstract or emerging concerns, such as the energy demands of blockchain or the transparency challenges posed by artificial intelligence, which did not surface in the interviews, possibly due to firms’ early-stage digital maturity or differing priorities.

These differences highlight the value of combining theoretical and empirical perspectives. Together, the interview and literature findings provide a more complete picture of the technical, institutional, and contextual challenges that shape digital transformation in the renewable energy sector.

5.9 Limitations of the Study

While this study provides a grounded and multi-perspective analysis of how digital technologies influence business model transformation in renewable energy firms, several limitations should be acknowledged.

First, the empirical base consists of five high-tech firms in the Netherlands, each represented by a single participant. While this enabled focused insights into digital strategies and transformation pathways, it limits within-firm triangulation and broader generalizability. Future studies could expand the scope across firm sizes, geographies, and market types.

Second, the interviews captured how business models evolved over time, but the data remains cross-sectional and relies on retrospective narratives. Longitudinal studies would be better positioned to observe real-time business model change and adaptation processes.

Third, the systematic literature review (SLR) primarily includes studies published between 2021 and 2024. This concentration reflects a recent surge in scholarly interest but may underrepresent earlier work due to keyword limitations or evolving terminology.

Fourth, while the study integrates both primary (interviews) and secondary (SLR) sources, the synthesis is interpretive. The Gioia methodology allows for structured insight-building, but also involves abstraction and researcher judgment, which may lead to loss of fine-grained mechanisms.

Fifth, the concept of integration depth, introduced as an analytical lens in this study, has not yet been formally validated through quantitative methods. It remains an exploratory construct and requires further development and testing.

Finally, the study’s geographic and linguistic scope was limited to English-language sources and firms operating within or relevant to the Netherlands and European context. Digitalization trajectories may differ significantly across other regions and infrastructural conditions.

These limitations offer opportunities for future research to extend, refine, and validate the findings presented here.

6 Conclusion

This chapter concludes the study by reflecting on its main findings and contributions. The research aimed to explore how digital technologies drive changes in the business models of high-tech renewable energy firms in the Netherlands , a topic of growing relevance as the sector faces simultaneous digital and energy transitions. While the operational role of digitalization is well recognized, its influence on how firms create, deliver, and capture value remains comparatively underexamined.

As a first step, the study identified the key digital technologies currently being utilized across the sector. It then examined how these technologies affect different business model components and how they relate to varying degrees of business model change. The remainder of this chapter summarizes the results in relation to the research questions and outlines the study’s contributions, implications, and future directions.

6.1 Summary of Research Design and Approach

To investigate how digital technologies shape business models in the renewable energy sector, the study employed a multi-method qualitative approach grounded in theory-building.

The research began with a narrative literature review to establish key concepts related to digital technologies, business model components, and business model change typologies. This was followed by a Systematic Literature Review (SLR) of 29 peer-reviewed articles published between 2015 and 2025. The SLR focused on extracting empirical observations of digitalization-related business model change, which were then analysed using the Gioia methodology.

In parallel, the study conducted five semi-structured interviews with Dutch firms operating in the renewable energy sector. Participants held strategic or technical leadership roles and shared insights into how digital technologies were being adopted and how their business models had evolved as a result. These interviews were coded using the same Gioia framework to allow comparison with the literature-based findings.

The analytical lens of the study combined two theoretical structures:

- The Business Model components: value creation, value delivery, and value capture.
- The Business Model Change Typology: adaptation (BMA), evolution (BME), and innovation (BMI), with an overarching lens of Business Model Dynamics (BMD) to capture non-linear and overlapping change trajectories.

This design enabled the study to generate structured insights grounded in both empirical literature and practice, while also identifying patterns and conceptual relationships through interpretive analysis.

6.2 Answers to Research Questions

RQ1: Which digital technologies are most influential?

The study identified several digital technologies that appear most prominently across both literature and interviews. These include Artificial Intelligence (AI), Internet of Things (IoT), Blockchain, Digital Twins, and Cloud Platforms. While their applications vary, these technologies emerged repeatedly as enablers of operational improvement, system coordination, personalization, and data-driven decision-making.

To better understand their role, the study grouped them into five functional categories based on their observed purpose in the sector:

- Group 1: Data Capture and Embedded Infrastructure (e.g., IoT, smart meters, edge devices)
- Group 2: Data Processing and System Intelligence (e.g., AI, ML, big data, digital twins)
- Group 3: Trust and Coordination Infrastructure (e.g., blockchain, smart contracts)
- Group 4: Customer Interface and Engagement Platforms (e.g., mobile apps, APIs, CRMs)
- Group 5: System-Level Orchestration and Simulation (e.g., VPPs, EMS, planning tools)

To synthesise these findings into a more interpretable structure, the study developed a conceptual layered grouping of digital technologies, shown in Figure 13.

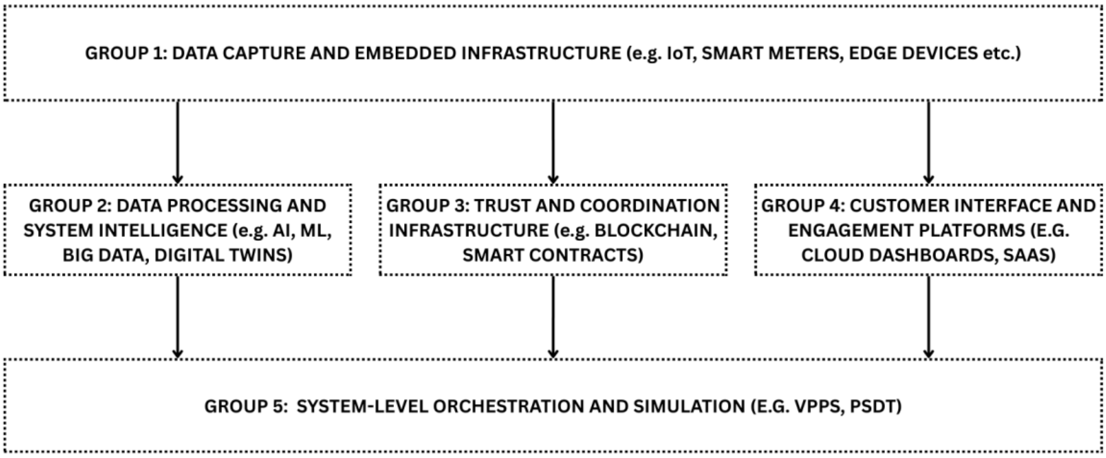

Figure 13. Conceptual layered grouping of digital technologies, synthesised from interviews and literature

The functional grouping developed in this study can be visualised as a layered technology stack. Group 1 represents the foundational layer of *data capture and embedded infrastructure*, including IoT devices, smart meters, and edge systems that generate the raw operational and environmental data required for digital processes. This data flows into Group 2, *data processing and system intelligence*, where AI, machine learning, big data analytics, and digital twins convert raw inputs into actionable insights. Group 3, *trust and coordination infrastructure*, encompasses technologies such as blockchain and smart contracts that validate, secure, and coordinate transactions or interactions between actors. Group 4, *customer interface and engagement platforms*, delivers processed and validated information to end-users through tools such as cloud dashboards, SaaS applications, and other engagement mechanisms. At the base, Group 5, *system-level orchestration and simulation*, integrates all preceding layers to enable large-scale coordination, such as virtual power plants (VPPs) or platform-based simulation and dispatch tools (PSDTs).

These groupings were derived through cross-case analysis of interview and literature data using the Gioia methodology. Rather than classifying technologies by their name or technical type, the study organised them based on the functional role they played in enabling business model change. As illustrated in Figure X, the groups are interdependent layers, where capabilities in one enable or enhance those above and below. This layered perspective clarifies how digital tools contribute to value creation, delivery, and capture, regardless of whether the tools were well-established (e.g., AI, IoT) or emerging (e.g., digital twins, blockchain).

Across both data sources, technologies were not used in isolation but often combined into multi-layered stacks (e.g., IoT + AI + CRM) spanning several parts of the business model. This pattern was particularly visible in cases where digital technologies were embedded across multiple business functions, as reflected in the layered architecture. While there was strong alignment between the technologies mentioned in interviews and those highlighted in the literature, especially for AI, IoT, and blockchain, some differences were also noted. The literature tended to include more forward-looking or speculative tools, such as quantum computing, augmented reality (AR/VR), or distributed computing, which were absent from the interview cases. This gap reflects both the exploratory nature of academic work and the practical focus of firms, which prioritised technologies that addressed current operational and market needs. Despite these differences, the functional grouping framework helped bridge this gap by emphasising technology roles over specific tools, allowing comparison across both datasets.

RQ2: How do digital technologies affect business model components?

Across both literature and interview data, digital technologies influenced all three business model components - value creation, value delivery, and value capture - though the depth and nature of impact varied significantly.

- **Value Creation** was the most consistently affected component. Technologies in Group 1 (Data Capture and Embedded Infrastructure) and Group 2 (System Intelligence) enabled real-time monitoring, predictive diagnostics, automation, and simulation , all of which contributed to improved efficiency and system-level control.
- **Value Delivery** saw substantial reconfiguration through Group 4 (Customer Interface and Engagement Platforms) and Group 5 (System-Orchestration and Simulation Tools). These enabled personalized service models, remote interaction, flexible access to energy services, and coordination across decentralized actors.
- **Value Capture** remained the least transformed component overall. However, meaningful changes were observed in cases leveraging Group 3 (Trust and Coordination Infrastructure) , such as blockchain-based P2P trading or traceability , and through monetization strategies built on Group 2 and 4 technologies (e.g., dynamic pricing, pay-as-you-go models).

Firms and cases that showed broader business model transformation typically combined technologies across multiple groups. These layered stacks allowed synergies between sensing, analytics, and interface layers , supporting more complex and service-oriented value propositions.

This suggests that the business model impact of digital technologies depends less on individual tools, and more on how coherently they are integrated across multiple components of the model.

In comparing the interview data with the literature, the overall patterns of how digital technologies influence business model components are largely consistent. Both datasets highlight that value creation is the most directly and consistently impacted, followed by delivery, with capture being the most complex to transform. The main difference lies in the breadth and maturity of use cases. Literature sources tend to describe more advanced or speculative applications, such as tokenized ownership, simulation-driven planning, or cooperative service platforms, particularly in relation to value capture and delivery. Interview cases, on the other hand, focus more on practical implementations tied to firm operations, such as onboarding automation, PAYG billing, or traceability for compliance. This suggests that while the underlying component-wise impacts are aligned, the literature reflects a more forward-looking scope, whereas interview cases reflect real-world limitations and current maturity levels.

RQ3: What types of business model changes (BMA, BME, BMI) are triggered?

The study found that **Business Model Evolution (BME)** was the most prevalent form of change. In both literature and interview cases, firms often adopted digital technologies incrementally to improve operations, coordination, and service delivery , without fundamentally altering their core value logic. This evolutionary change was especially common in cases where technologies were layered progressively over time.

Business Model Adaptation (BMA) was also observed, particularly in response to practical or infrastructural limitations. In some cases, firms adopted lightweight or offline-compatible digital solutions to address connectivity gaps , for example, implementing short-range data transfer (e.g., via Bluetooth) to collect system information locally when real-time transmission was not feasible due to unreliable network conditions. These adaptations were often reactive and modular, aimed at solving specific operational challenges without broader business model restructuring.

Business Model Innovation (BMI), while less common, was clearly present in select cases where digital technologies formed the basis of new offerings or ecosystem roles. This included examples like tokenized platforms, blockchain-enabled traceability, or digital-first service bundles. These innovations typically involved deeper digital embedding across creation, delivery, and capture.

Importantly, many cases showed combinations of BMA, BME, and BMI coexisting within the same organization. This supports a Business Model Dynamics (BMD) view, where business model change is not linear but layered, recursive, and context-dependent. One of the study's key observations is that Business Model Innovation (BMI) most often occurred when digital technologies from multiple functional groups were deployed in combination. For example, Firms C, D, and E used stacks combining Group 1 (infrastructure), Group 2 (intelligence), Group 3 (trust systems), and Group 4 (user interfaces) to trigger concurrent shifts in value creation, delivery, and capture. In contrast, isolated or single-group deployments typically aligned with BME or BMA. This suggests that it is not the specific technology itself, but their functional diversity and strategic layering across business model components, that tends to drive innovation.

One of the study's key insights is the emergence of **Digital Integration Depth** as a potential explanatory lens. Firms and cases that demonstrated deeper and more strategic integration of digital technologies across their business model architecture were more likely to show signs of BMI.

When comparing the literature and interview cases, the classification of business model change types showed broad convergence. Both sources identified BME as the most prevalent form, often driven by gradual digital layering. However, literature examples tended to present more abstract and sector-level visions of BMI, such as tokenized ecosystems or decentralized markets, while the interview cases reflected more grounded forms of innovation, like cloud-first platforms or PAYG models. BMA also appeared in both, typically linked to infrastructural or regulatory constraints. Overall, the main difference lay in framing: the literature emphasized conceptual possibilities, while interviews revealed operational realities.

6.3 Theoretical Contributions

This study contributes to the growing body of research on digitization and business model change by offering a structured, component-level understanding of how digital technologies influence the business models of firms operating in the renewable energy sector. While digital transformation is increasingly discussed in this field, its relationship to business model change remains relatively underexplored, particularly in the context of high-tech firms engaging with emerging digital infrastructures. By combining the business model change typology (BMA, BME, BMI) with the components of value creation, delivery, and capture, the study extends existing frameworks by applying them in the context of high-tech renewable energy firms, where such applications have so far been limited. The analysis was grounded in both literature and interview data, allowing for a nuanced view of how change plays out in practice as well as how it is conceptualized in published research.

A key theoretical contribution lies in the functional grouping of digital technologies developed from the synthesis of findings from both the interviews and the systematic literature review. Organising technologies into functional groups arranged from data collection to orchestration reduces construct heterogeneity, provides a clear link to value creation, delivery, and capture, and offers an explicit basis for examining how combinations of technology layers relate to different types of business model change. This grouping is positioned as a testable lens that future research can apply to compare findings across different contexts or to explore whether specific configurations of layers are associated with particular change outcomes. The study also reinforces the relevance of the Business Model Dynamics perspective by showing that change is rarely linear or discrete; instead, firms often move through overlapping phases of adaptation, evolution, and innovation depending on their context. In addition, the concept of digital integration depth emerged from the empirical analysis as a potentially useful way to understand why some firms are able to leverage digital technologies for deeper business model innovation, while others remain at a more incremental level. While still exploratory, this concept provides a foundation for further theorisation and empirical testing, particularly in relation to its connection with different business model change types. The findings indicate that integration depth appears to be more strongly linked with the emergence of BME and especially BMI, whereas BMA is often driven by contextual or infrastructural constraints and does not correlate as directly with the degree of digital embedding.

6.4 Practical Implications

For firms, the functional grouping of technologies derived from both empirical and literature evidence offers more than a descriptive classification; it can be operationalised as a framework for strategic decision-making. Firms can map their existing assets to the layers of the grouping, identify capability gaps relative to targeted business model changes, and design a staged adoption path in which upstream data quality and interoperability enable downstream service models and new revenue opportunities. Used alongside the concept of digital integration depth, this framework allows firms to test whether adding or strengthening specific layers correlates with shifts from BMA to BME or BMI, making digital investment choices more evidence-based and less reliant on trial-and-error. While modular tools such as dashboards, APIs, and CRM systems can deliver short-term efficiency gains, deeper business model innovation is more likely when technologies are embedded across multiple layers of operations and business model structure. Such layered adoption facilitates synergies between sensing, analytics, and customer engagement, supporting more service-oriented and scalable offerings. Strategic partnerships, such as those with blockchain-based traceability providers or platform solution vendors, can also help bridge internal capability gaps and accelerate digital integration.

For policymakers and supporting institutions, the results highlight the importance of investing in foundational digital infrastructure, including reliable connectivity, interoperable systems, and secure data environments. Flexible regulatory frameworks are needed to enable experimentation with new business models, such as peer-to-peer energy trading and tokenised revenue structures. Targeted support for small and mid-sized firms through training, funding, or shared infrastructure can help to address legacy system constraints that limit digital adoption. Furthermore, while not yet mainstream, emerging technologies such as digital twins, augmented and virtual reality, and quantum-enabled systems may create new opportunities for experimentation and business model redesign in the future.

6.5 Limitations and Directions for Future Research

As with any exploratory qualitative study, this research has certain limitations that also suggest directions for further work.

First, the empirical base of five high-tech firms in the Netherlands, each represented by a single participant, provides depth but limits broad generalisability. Future research could apply this framework to a wider variety of renewable energy firms or extend it into other infrastructure-heavy sectors facing similar digitalisation challenges, such as water, waste, or mobility. These adjacent sectors often share legacy system constraints and decentralised architectures, making them well-suited for comparative exploration.

Second, although the interviews captured how firms' business models evolved over time, the data remains cross-sectional and relies on retrospective narratives. Longitudinal studies that follow firms through digital transitions in real time could provide more detailed insights into how business model adaptation, evolution, and innovation unfold and how these shifts interact with external developments.

Third, this study relied on interpretive coding using the Gioia methodology. While this enabled clarity at the level of aggregate dimensions, some granularity may have been lost in the process of abstraction. Future work could complement such interpretive approaches with mixed-method or quantitative studies to assess the prevalence or causal relationships between technology use and business model change.

Finally, the concept of digital integration depth emerged inductively from the combined interview and literature data as a potentially useful way to explain variation in the degree of change observed across cases. While it proved valuable for interpreting cross-case patterns, it remains an exploratory construct. Future work could further develop and validate this idea by operationalising levels of digital integration and testing their relationship to different types of business model transformation. Similarly, the five functional technology groupings, while grounded in observed patterns from both datasets, have not yet been benchmarked against established classification systems. Future work could refine these groupings and test their relevance across broader datasets.

Building on these limitations, future research should explore the concept of digital integration depth not only as an analytical lens but also as a potential predictive factor in business model change. This requires examining both the selection of technologies and the extent to which they are coherently embedded across value creation, delivery, and capture mechanisms. Understanding these patterns at the firm level can provide a more detailed view of how digital transformation unfolds over time. From this perspective, a core research question emerges:

How does the depth of digital technology integration influence the type and trajectory of business model change in renewable energy firms?

Beyond this central focus, the combined literature and interview analyses reveal several additional thematic gaps that offer promising directions for further inquiry. These are summarised in Table 8, which organises underexplored areas and corresponding research questions into three overarching themes.

Table 8. Future Research Questions

Main Theme	Gaps / Underexplored Areas	Potential Research Questions
Business Model Dynamics in the Renewable Energy Sector	1. Lack of longitudinal studies mapping sequential business model changes. 2. Limited understanding of transitions between BMA, BME, and BMI in real firms.	RQ1: How do renewable energy firms transition between adaptation, evolution, and innovation in response to digital integration? RQ2: What patterns of business model dynamics emerge over time in digitally transforming energy firms?
Digital Integration Pathways	1. Absence of defined growth logic in layering digital technologies. 2. Unclear how integration depth evolves and influences business model change types.	RQ3: What are the typical sequences and patterns of digital technology adoption in renewable energy firms? RQ4: How does the order and maturity of digital technology

Main Theme	Gaps / Underexplored Areas	Potential Research Questions
		integration influence the type and trajectory of business model change?
Firm-Level Conditions for Transformation	1. Variability in transformation between startups and incumbents. 2. Underexplored enablers such as capabilities, leadership, and regulation.	RQ5: How do firm size, digital capabilities, and external conditions shape the relationship between digital technologies and business model change in the renewable energy sector?

These proposed research avenues extend the conceptual foundation developed in this study and open opportunities for comparative, longitudinal, and firm-level investigations. Empirical exploration of these questions could build a more nuanced understanding of digital transformation processes and provide actionable insights for both academic theorisation and strategic decision-making in renewable energy and related sectors.

6.6 Final Reflections

This study set out to examine how digital technologies influence business model change in high-tech renewable energy firms, a question of growing importance as the energy sector navigates simultaneous digital and sustainable transitions. By combining a systematic literature review with empirical insights from five diverse cases, and applying the Gioia methodology to both datasets, the research delivers an integrated, evidence-based perspective that has so far been absent in this field.

The findings show that while digital tools are increasingly embedded in renewable energy operations, their business model impacts vary considerably across contexts. Most observed changes were evolutionary, with firms progressively layering technologies to strengthen operational efficiency, customer engagement, and service offerings. Business model innovation, where digital technologies fundamentally redefine value creation, delivery, and capture, was less frequent but clearly visible in cases where digital adoption was both deep and coherent across multiple business model components. This reinforces the Business Model Dynamics (BMD) perspective, highlighting that adaptation, evolution, and innovation often co-exist and overlap, rather than unfold as discrete stages.

Two original contributions stand out. First, the functional grouping of digital technologies, derived from both literature and interviews, offers a clear and transferable framework for assessing technology roles in business model change. Organised from upstream data capture to downstream orchestration, this grouping not only reduces conceptual ambiguity but also provides a testable lens for linking technology configurations to specific business model outcomes. Second, the concept of digital integration depth, introduced and explored in this study, offers a novel way to interpret why some firms achieve deeper transformation while others remain incremental. The findings suggest that higher integration depth is associated with more ambitious forms of change such as BME and BMI, while BMA is more often shaped by external constraints such as infrastructure and regulation.

Beyond these individual contributions, the integration of SLR and interview findings into a unified analytical framework, encompassing both functional groupings and integration depth, creates a foundation for future research that is both conceptually grounded and practically applicable. The framework provides practitioners with a diagnostic tool to map their current digital maturity, identify strategic gaps, and sequence technology adoption for maximum business model impact.

As the renewable energy sector continues to evolve, firms will need to move beyond isolated tool adoption and engage with the architectural and system-level design of their business models. Understanding not just what technologies are adopted but how they are embedded and layered will be critical for unlocking new sources of value and sustaining competitive advantage.

In conclusion, this thesis offers a richer and more structured understanding of digital business model change in the renewable energy sector, bridging conceptual insight with actionable guidance. By introducing and operationalising the concepts of functional technology grouping and digital integration depth, it advances both theory and practice, opening pathways for empirical testing and cross-sector application. These contributions position the study as a reference point for future work seeking to explain and shape the digital transformation of energy systems.

7 References

Ahmad, T., Zhang, D., Huang, C., Zhang, H., Dai, N., Song, Y., & Chen, H. (2021). Artificial intelligence in sustainable energy industry: Status Quo, challenges and opportunities. Journal of Cleaner Production, 289, 125834. https://doi.org/10.1016/j.jclepro.2021.125834

Amit, R., & Zott, C. (2010). Business model innovation: Creating value in times of change. IESE Insight, (8), 16–25

Amit, R., & Zott, C. (2012). Creating value through business model innovation. MIT Sloan management review.

Augello, A., Gallo, P., Sanseverino, E. R., Sciumè, G., & Tornatore, M. (2022). A Coexistence Analysis of Blockchain, SCADA Systems, and OpenADR for Energy Services Provision. IEEE Access, 10, 99088–99101. https://doi.org/10.1109/ACCESS.2022.3205121

Bähr, K., & Fliaster, A. (2023). The twofold transition: Framing digital innovations and incumbents' value propositions for sustainability. Business Strategy and the Environment, 32(2), 920–935. https://doi.org/10.1002/bse.3082

Balboni, B., & Bortoluzzi, G. (2015). Business model adaptation and the success of new ventures. Journal of Business Research, 68(7), 1534–1538

Bartczak, K. (2021). Digital Technology Platforms as an Innovative Tool for the Implementation of Renewable Energy Sources. Energies, 14(23), 7877. https://doi.org/10.3390/en14237877

Bartczak, K., & Łobejko, S. (2022). The Implementation Environment for a Digital Technology Platform of Renewable Energy Sources. Energies, 15(16), Article 16. https://doi.org/10.3390/en15165793

Baumeister, R. F., & Leary, M. R. (1997). Writing narrative literature reviews. Review of General Psychology, 1(3), 311–320. https://doi.org/10.1037/1089-2680.1.3.311

Birt L, Scott S, Cavers D, Campbell C, Walter F. Member Checking: A Tool to Enhance Trustworthiness or Merely a Nod to Validation? Qualitative Health Research. 2016;26(13):1802-1811. doi:10.1177/1049732316654870

Carayannis, E. G., Sindakis, S., & Walter, C. (2015). Business Model Innovation as Lever of Organizational Sustainability. Journal of Technology Transfer, 40(1), 85–104. https://doi.org/10.1007/S10961-013-9330-Y

Cavalcante, S., Kesting, P., & Ulhøi, J. P. (2011). Business model dynamics and innovation: (Re)establishing the missing linkages. Journal of Business Models, 1(1), 85–105.

Chanyasak, C., & Watanabe, C. (2023). Business model adaptation in the hospitality industry: A response to COVID-19. Tourism Management Perspectives, 45, 101045

Chesbrough, H. (2010). Business model innovation: Opportunities and barriers. Long Range Planning, 43(2–3), 354–363. https://doi.org/10.1016/j.lrp.2009.07.010

Ciano, M. P., Peron, M., Panza, L., & Pozzi, R. (2025). Industry 4.0 technologies in support of circular Economy: A 10R-based integration framework. Computers & Industrial Engineering, 201, 110867. https://doi.org/10.1016/j.cie.2025.110867

Ciulli, F., Kolk, A., Bidmon, C. M., Sprong, N., & Hekkert, M. P. (2022). Sustainable business model innovation and scaling through collaboration. Environmental Innovation and Societal Transitions, 45, 289–301. https://doi.org/10.1016/j.eist.2022.11.003

Cooperative digital platforms in the renewable energy sector. (2023). INTELLECTUAL ECONOMICS. https://doi.org/10.13165/IE-24-18-1-10

Dada, O. L. (2018). A model of entrepreneurial autonomy in franchised outlets: A systematic review of the empirical evidence. *International Journal of Management Reviews, 20*(2), 206–226. https://doi.org/10.1111/ijmr.12123

D'Amore, G., Di Vaio, A., Balsalobre-Lorente, D., & Boccia, F. (2022). Artificial Intelligence in the Water–Energy–Food Model: A Holistic Approach towards Sustainable Development Goals. Sustainability, 14(2), Article 2. https://doi.org/10.3390/su14020867

Demil, B., & Lecocq, X. (2010). Business model evolution: In search of dynamic consistency. *Long Range Planning, 43*(2–3), 227–246. https://doi.org/10.1016/j.lrp.2010.02.004

Del Vecchio, P., Massaro, A., & Garzoni, A. (2025). Circular value creation and business process management for twin transition: The case of an energy company. Computers & Industrial Engineering, 201, 110936. https://doi.org/10.1016/j.cie.2025.110936

Endres, S., & Weibler, J. (2017). Towards a three-component model of relational social constructionist leadership: A systematic review and critical interpretive synthesis. *International Journal of Management Reviews, 19*(2), 214–236. https://doi.org/10.1111/ijmr.12095

Foss, N. J., & Saebi, T. (2017). Fifteen years of business model innovation research: Past accomplishments, future challenges. Journal of Management, 43(1), 200–227. https://doi.org/10.1177/0149206316675927

Foss, N. J., & Saebi, T. (2018). Business models and business model innovation: Between wicked and paradigmatic problems. Long Range Planning, 51(1), 9–21. https://doi.org/10.1016/j.lrp.2017.07.006

Franki, V., Majnarić, D., & Višković, A. (2023). A Comprehensive Review of Artificial Intelligence (AI) Companies in the Power Sector. Energies, 16(3), Article 3. https://doi.org/10.3390/en16031077

Gehman, J., Glaser, V. L., Eisenhardt, K. M., Gioia, D. A., Langley, A., & Corley, K. G. (2018). Finding theory–method fit: A comparison of three qualitative approaches to theory building. *Journal of Management Inquiry, 27*(3), 284–300.

Geissdoerfer, M., Vladimirova, D., & Evans, S. (2018). Sustainable business model innovation: A review. Journal of Cleaner Production, 198, 401–416.

Gioia, D. A., Corley, K. G., & Hamilton, A. L. (2013). Seeking qualitative rigor in inductive research: Notes on the Gioia methodology. *Organizational Research Methods, 16*(1), 15–31. https://doi.org/10.1177/1094428112452151

Gitelman, L., & Kozhevnikov, M. (2023). New business models in the energy sector in the context of revolutionary transformations. *Sustainability, 15*(4), 1–22. https://doi.org/10.3390/su15043423

Guckenbiehl, P., & Corral De Zubielqui, G. (2022). Start-ups' business model changes during the COVID-19 pandemic: Counteracting adversities and pursuing opportunities. International Small Business Journal: Researching Entrepreneurship, 40(2), 150–177

Hu, B., Zhou, P., & Zhang, L. P. (2022). A digital business model for accelerating distributed renewable energy expansion in rural China. Applied Energy, 316, 119084. https://doi.org/10.1016/j.apenergy.2022.119084

K. N., A. S. I., S., M., Desai, K., S., H. K., & Kautish, S. (2024). Optimizing Green Power and Green Energy Through Digital Technologies. In W. Leal Filho, S. Kautish, T. Wall, S. Rewhorn, & S. K. Paul (Eds.), Digital Technologies to Implement the UN Sustainable Development Goals (pp. 275–304). Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-68427-2_14

Kallio, H., Pietilä, A. M., Johnson, M., & Kangasniemi, M. (2016). Systematic methodological review: Developing a framework for a qualitative semi-structured interview guide. *Journal of Advanced Nursing, 72*(12), 2954–2965. https://doi.org/10.1111/jan.13031

Khodaei, H., & Ortt, R. (2019). Capturing dynamics in business model frameworks. Journal of Open Innovation: Technology, Market, and Complexity, 5(1), 8. https://doi.org/10.3390/joitmc5010008

Laur, I., & Berntzen, L. (2023). Opposing forces of business model innovation in the renewable energy sector: Alternative patterns and strategies. The International Journal of Entrepreneurship and Innovation, 14657503231194727. https://doi.org/10.1177/14657503231194727

Leiva Vilaplana, J. A., Yang, G., Monaco, R., Bergaentzlé, C., Ackom, E., & Morais, H. (2025). Digital versus grid investments in electricity distribution grids: Informed decision-making through system dynamics. Applied Energy, 386, 125536. https://doi.org/10.1016/j.apenergy.2025.125536

Lepak, D. P., Smith, K. G., & Taylor, M. S. (2007). Value creation and value capture: A multilevel perspective. Academy of Management Review, 32(1), 180–194. https://doi.org/10.5465/amr.2007.23464011

Liu, J., Huang, Z., Fan, M., Yang, J., Xiao, J., & Wang, Y. (2022). Future energy infrastructure, energy platform and energy storage. Nano Energy, 104, 107915. https://doi.org/10.1016/j.nanoen.2022.107915

Malewska, K., Cyfert, S., Chwiłkowska-Kubala, A., Mierzejewska, K., & Szumowski, W. (2024). The missing link between digital transformation and business model innovation in energy SMEs: The role of digital organisational culture. Energy Policy, 192, 114254. https://doi.org/10.1016/j.enpol.2024.114254

Markides, C. (2006). Disruptive innovation: In need of better theory. Journal of Product Innovation Management, 23(1), 19–25. https://doi.org/10.1111/j.1540-5885.2005.00177.x

Massa, L., Tucci, C. L., & Afuah, A. (2017). A critical assessment of business model research. Academy of Management Annals, 11(1), 73–104. https://doi.org/10.5465/annals.2014.0072

McGrath, R. G. (2010). Business models: A discovery driven approach. Long Range Planning, 43(2–3), 247–261. https://doi.org/10.1016/j.lrp.2009.07.005

Mika, B., & Goudz, A. (2021). Blockchain-technology in the energy industry: Blockchain as a driver of the energy revolution? Energy Reports, 7, 4511–4524. https://doi.org/10.1016/j.egyr.2021.07.028

Muhammad Adnan, Zahid, H., Zulfiqar, A., Sajid Iqbal, M., Shah, A., & Fida, K. (2024). Global Renewable Energy Transition: A Multidisciplinary Analysis of Emerging Computing Technologies, Socio-Economic Impacts, and Policy Imperatives. https://doi.org/10.31224/4112

Neska, E., & Kowalska-Pyzalska, A. (2022). Digitalization and energy transformation: Towards energy democracy or energy technocracy? *Energy Research & Social Science, 89*, 102548. https://doi.org/10.1016/j.erss.2022.102548

Osterwalder, A., & Pigneur, Y. (2010). Business model generation: A handbook for visionaries, game changers, and challengers. John Wiley & Sons.

Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., ... & Moher, D. (2021). The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *BMJ, 372*, n71. https://doi.org/10.1136/bmj.n71

Pakulska, T., & Poniatowska-Jaksch, M. (2022). Digitalization in the Renewable Energy Sector—New Market Players. Energies, 15(13), 4714. https://doi.org/10.3390/en15134714

Patton, M. Q. (2002). *Qualitative research and evaluation methods* (3rd ed.). SAGE Publications.

Peñarroya-Farell, M., & Miralles, F. (2021). Business model dynamics from interaction with open innovation. *Journal of Open Innovation: Technology, Market, and Complexity, 7*(1), 81. https://doi.org/10.3390/joitmc7010081

Philippi, S., Heinz, A., & Kabous, L. (2022). How Swiss start-ups deal with business model innovation. *European Conference on Innovation and Entrepreneurship, 17*, 408–415. https://doi.org/10.34190/ecie.17.1.534

Plewnia, F. (2019). The Energy System and the Sharing Economy: Interfaces and Overlaps and What to Learn from Them. Energies, 12(3), Article 3. https://doi.org/10.3390/en12030339

Rasagam, G., & Zhu, D. (2018). Delivering on the Promise of Distributed Renewable Energy Entrepreneurship in Sub-Saharan Africa. Current Sustainable/Renewable Energy Reports, 5(4), 230–239. https://doi.org/10.1007/s40518-018-0120-x

Richardson, J. (2008). The business model: An integrative framework for strategy execution. Strategic Change, 17(5–6), 133–144. https://doi.org/10.1002/jsc.821

Saebi, T. (2014). Business model evolution, adaptation or innovation? A contingency framework. *Social Science Research Network*. https://doi.org/10.2139/ssrn.2403151

Saebi, T., Lien, L., & Foss, N. J. (2017). What drives business model adaptation? The impact of opportunities, threats and strategic orientation. Long Range Planning, 50(5), 567–581. https://doi.org/10.1016/j.lrp.2016.06.006

Shenton, A. (2004). Strategies for Ensuring Trustworthiness in Qualitative Research Projects. Education for Information, 22, 63–75. https://doi.org/10.3233/EFI-2004-22201

Singh, M., Jiao, J., Klobasa, M., & Frietsch, R. (2021). Making Energy-transition headway: A Data driven assessment of German energy startups. Sustainable Energy Technologies and Assessments, 47, 101322. https://doi.org/10.1016/j.seta.2021.101322

Skaloumpakas, P., Sarmas, E., Rachmanidis, M., & Marinakis, V. (2024). Reshaping the energy landscape of Crete through renewable energy valleys. Scientific Reports, 14(1), 8038. https://doi.org/10.1038/s41598-024-57471-7

Spieth, P., Schneckenberg, D., & Ricart, J. E. (2014). Business model innovation – state of the art and future challenges for the field. R & D Management, 44(3), 237–247. https://doi.org/10.1111/RADM.12071

Sosna, M., Trevinyo-Rodríguez, R. N., & Velamuri, S. R. (2010). Business model innovation through trial-and-error learning. Long Range Planning, 43(2–3), 383–407. https://doi.org/10.1016/j.lrp.2010.02.003

Sułek, A., & Borowski, P. F. (2024). Barriers and challenges to the digital transformation of the energy sector in the EU. *Energies, 17*(1), Article 67. https://doi.org/10.3390/en17010067

Teece, D. J. (2010). Business models, business strategy and innovation. *Long Range Planning, 43*(2–3), 172–194. https://doi.org/10.1016/j.lrp.2009.07.003

Teece, D. J. (2018). Business models and dynamic capabilities. *Long Range Planning, 51*(1), 40–49. https://doi.org/10.1016/j.lrp.2017.06.007

Timmermans, S., & Tavory, I. (2012). Theory construction in qualitative research: From grounded theory to abductive analysis. *Sociological Theory, 30*(3), 167–186. https://doi.org/10.1177/0735275112457914

Tranfield, D., Denyer, D., & Smart, P. (2003). Towards a methodology for developing evidence-informed management knowledge by means of systematic review. *British Journal of Management, 14*(3), 207–222. https://doi.org/10.1111/1467-8551.00375

Trischler, J., & Li-Ying, J. (2022). Digital transformation and business model innovation: A sectoral review. *Journal of Business Research, 146*, 1–13. https://doi.org/10.1016/j.jbusres.2022.03.024

Venkatachary, S. K., Prasad, J., & Samikannu, R. (2017). Challenges, Opportunities and Profitability in Virtual Power Plant Business Models in Sub Saharan Africa—Botswana. International Journal of Energy Economics and Policy, 7(4), Article 4.

Vom Scheidt, F., & Staudt, P. (2024). A data-driven Recommendation Tool for Sustainable Utility Service Bundles. Applied Energy, 353, 122137. https://doi.org/10.1016/j.apenergy.2023.122137

Wang, Y., Li, Y., & Zhao, D. (2025). Digital transformation in energy enterprises: Drivers, enablers, and business model reconfigurations. *Journal of Cleaner Production, 412*, 137221. https://doi.org/10.1016/j.jclepro.2025.137221

Wirtz, B. W., Pistoia, A., Ullrich, S., & Göttel, V. (2016). Business models: Origin, development and future research perspectives. Long Range Planning, 49(1), 36–54. https://doi.org/10.1016/j.lrp.2015.04.001

Yu, Y., Ren, F., Ju, Y., Zhang, J., & Liu, X. (2024). Exploring the Role of Digital Transformation and Breakthrough Innovation in Enhanced Performance of Energy Enterprises: Fresh Evidence for Achieving Sustainable Development Goals. Sustainability, 16(2), 650. https://doi.org/10.3390/su16020650

Zhao, Y., Xia, S., Zhang, J., Hu, Y., & Wu, M. (2021). Effect of the Digital Transformation of Power System on Renewable Energy Utilization in China. IEEE Access, 9, 96201–96209. https://doi.org/10.1109/access.2021.3094317

Zott, C., Amit, R., & Massa, L. (2011). The business model: Recent developments and future research. Journal of Management, 37(4), 1019–1042. https://doi.org/10.1177/0149206311406265

Zott, C., & Amit, R. (2013). The business model: A theoretically anchored robust construct for strategic analysis. Strategic Organization, 11(4), 403-411. https://doi.org/10.1177/1476127013510466 (Original work published 2013)

Appendix A – Key Concepts Literature Overview

Table A.1 Business Model Adaptation (BMA): Definitions and Key Insights from Literature

Paper	Definition / Key Insights
Balboni & Bortoluzzi (2015)	BMA is a capability that enables survival in dynamic environments. Emerges from sensing customer needs, market misalignments, and technological potential.
Sosna et al. (2010)	BMA is part of trial-and-error learning; involves continuous fine-tuning and adaptation. Enables robustness and scalability; driven by iterative learning.
Massa, Tucci, & Afuah (2017)	Firms reconfigure business models incrementally in response to environmental change. Especially when facing disruption or environmental pressure.
Saebi, Lien & Foss (2017)	Defined as 'the process by which a firm actively aligns its business model in response to environmental change'. Focuses on short-term adjustment and environmental fit.
Guckenbiehl & Corral de Zubielqui (2022)	BMA is a response mechanism to external disruptions like COVID-19. Enables firms to maintain value creation in changing conditions.
Carayannis, Sindakis, & Walter (2015)	Business model adaptation is described as an organization's effort to align its model with internal and external changes. The paper notes that BMA enables firms to stay flexible and responsive to shifting technologies and customer values, allowing incremental reconfiguration without fundamentally altering the core business logic.

***NOTE: Definitions of BMA used in this study are based on prior literature but were carefully adapted to ensure conceptual clarity and empirical usability. We selected only those framings that could be consistently distinguished based on scope and depth of change, while avoiding overlapping or ambiguous formulations that could blur the lines between categories.*

Table A.2 Business Model Evolution (BME): Definitions and Key Insights from Literature

Paper	Definition / Key Insights
Demil & Lecocq (2010)	Business model evolution is a fine-tuning processinvolving both intended and emergent changes within and between business model components. Observable signs include structural shifts in cost/revenue models, often triggered by environmental dynamics or operational feedback loops.
Saebi, Lien & Foss (2017)	BME refers to gradual, progressive change reflecting continuous learning and adjustment. Part of a lifecycle view of BMs; contrasts with reactive adaptation and radical innovation.
Sosna et al. (2010)	BME emerges through trial-and-error learning, where firms evolve their BM over time. Includes iterative experiments leading to sustainable value creation and operational renewal.
Balboni & Bortoluzzi (2015)	BME is implied as part of the longitudinal development of business models among international ventures. Highlighted through gradual shifts and improvement of business configuration over early-stage years.
Foss & Saebi (2018)	Described as a fine-tuning process involving voluntary and emergent changes in and between core components. Emphasizes that evolution is a natural process, distinct from the disruptive reconfiguration associated with innovation.
Wirtz et al. (2016)	BME is about gradual change over time, including continuous adaptations to resources, offerings, and internal processes. Evolution is framed as learning-based and ongoing, enabling firms to stay competitive by refining how value is delivered or created.
McGrath (2010)	Business models are not static; they must evolve over time to adapt to changing market constraints, technologies, and customer needs Emphasizes that existing models are continually tested and refined to remain viable in dynamic environments.

Khodaei & Ortt (2019)	BME is discussed in terms of progressive refinements and iterative changes to develop internal consistency or adapt to environmental pressures. - "A BM that is sustainable over time is rarely found immediately…" - BME is part of the dynamic process leading toward innovation. - Highlights how BM change can emerge from either deliberate shifts or cumulative adaptation.

***NOTE: Definitions of BME used in this study are based on prior literature but were carefully adapted to ensure conceptual clarity and empirical usability. We selected only those framings that could be consistently distinguished based on scope and depth of change, while avoiding overlapping or ambiguous formulations that could blur the lines between categories.*

Table A.3 Business Model Innovation (BMI): Definitions and Key Insights from Literature

Paper	Definition / Key Insights
Amit & Zott (2010)	BMI involves designing a modified or new activity system, often by recombining existing resources across the firm and its partners. BMI can be enabled by ICT (e.g., broadband) but doesn't require new R&D; focuses on re-structuring exchanges and interactions across firm boundaries.
Chesbrough (2010)	BMI is the process through which firms develop new ways of creating, delivering, and capturing value from their technologies and ideas.
Foss & Saebi (2017)	BMI entails designed, novel, non-trivial changesto a firm's business model components or their linkages. They distinguish BMI from operational changes; novelty and architectural impact are critical.
Markides (2006)	BMI is the discovery of a fundamentally different business model in an existing business. Must enlarge the economic piee.g., by attracting new customers or re-defining how value is delivered.
Massa et al. (2017)	BMI is a new dimension of innovation, distinct from product or process innovation, focused on new ways of organizing business activities. Includes models like platforms that govern economic and social interactions,not just tangible output.
Sosna et al. (2010)	BMI occurs through trial-and-error learning, involving experimentation, evaluation, and gradual refinement. It is not top-down; learning is distributed across the firm's levels and unfolds in phases (e.g., experimentation to exploitation).
Saebi, Lien & Foss (2017)	BMI is defined as a radical reconfiguration of business architecture, driven by internal motivations and strategic intent. Distinguished from adaptation (incremental response) and evolution (gradual change).

Chanyasak & Watanabe (2023)	BMI is described as replacing a business model to provide customers with previously unavailable products/services. Invokes reassessment of what constitutes value; triggered by major disruptions like COVID-19.
Foss & Saebi (2018)	BMI involves novel, designed, non-trivial changes, with modular or architectural scope and a spectrum from new-to-firm to new-to-industry. Emphasizes intentionality, scope, and degree of novelty.
Teece (2018)	BMI is a continuous process involving design, testing, and refinement of business models. Enabled by dynamic capabilities like sensing, seizing, transforming; often involves remixing components into hybrid models.
Wirtz et al. (2016)	BMI refers to fundamentally rethinking and reinventing the BM, beyond incremental adjustments. Triggered by disruptive innovation; results in reconfiguring how firms create/deliver value, potentially reshaping industries.
McGrath (2010)	BMI is positioned as a discovery-driven process, where new models are developed through iterative learning, experimentation, and testing.
Spieth, Schneckenberg, & Ricart (2014)	Business model innovation is defined as “the discovery of a fundamentally different business model in an existing business” (Markides, 2006, p. 20), and as “the search for new business logics of the firm and new ways to create and capture value for its stakeholders” (Casadesus-Masanell & Zhu, 2013, p. 464). highlights BMI as a critical driver of firm-level value creation and value capture. The focus is on exploring novel business logics and architectures, not just incremental improvements.
Carayannis, Sindakis, & Walter (2015)	BMI involves reconfiguring activities in a firm's existing business model to introduce new products or services. It is framed as a lean innovation method leveraging existing resources. The paper describes how BMI helps firms launch new offerings with limited investment by reorganizing internal resources and processes. It presents BMI as central to organizational sustainability and strategic renewal.

Khodaei & Ortt (2019)	BMI is described as a strategic process driven by higher-order dynamic capabilities (sensing, seizing, transforming). It involves reconfiguring BM components and their interrelations. - Emphasizes that success is not only about product innovation, but also about innovative BMs. - “BM innovation is a strategic process… based on dynamic capabilities.” - BMs can act as entrepreneurial mechanisms to exploit opportunities. - Innovation may result in entirely new BM configurations.

***NOTE: Definitions of BMI used in this study are based on prior literature but were carefully adapted to ensure conceptual clarity and empirical usability. We selected only those framings that could be consistently distinguished based on scope and depth of change, while avoiding overlapping or ambiguous formulations that could blur the lines between categories.*

Table A.4 Business Model Dynamics (BMD): Definitions and Key Insights from Literature

Paper	Definition / Key Insights
Cavalcante et al. (2011)	BMD describes continuous changes in core processes due to internal and external forces. Emphasizes interplay between structure and flexibility in BM change.
Demil & Lecocq (2010)	Dynamic consistency is about how BMs evolve dynamically through interactions between BM elements, triggers, and consistency. Dynamic consistency ensures performance during change.
Saebi, Lien & Foss (2017)	BMD captures multiple dimensions of how BMs change over time,via adaptation, evolution, and innovation. Reflects firm responses to external shocks and internal strategies.
Foss & Saebi (2018)	BMD refers to how the structure and interdependence of BM components change and affect performance. Highlights complementarities and structural tensions during change.
Wirtz et al. (2016)	The dynamic perspective on business models emphasizes that they are not static but continually in a state of flux due to technology, competition, and market pressures. Business model dynamics incorporate the life cycle of a business model, which includes both evolutionary adjustments and innovative leaps. Dynamics highlight how the interrelations between components (e.g., strategy, resources, customer interaction) change over time
Carayannis, Sindakis, & Walter (2015)	Business models are portrayed as dynamic systems that evolve in response to internal and external forces. Emphasizes that business models are not static,they reflect current organizational states and adapt continuously. Highlights the need to consider business models as part of a firm's dynamic alignment with strategy and market conditions.

Khodaei & Ortt (2019)	BMD is defined as "the frequency and degree of changes in the business model." It captures how often and how significantly business models change over time. - BMD includes learning, evolution, innovation, renewal, replication, and erosion. - Dynamic frameworks must account for completeness, interrelationships, interrelationships over time, and framework changes. - BMs are influenced by technological change, market shifts, and internal strategy. - Start-ups, especially in high-tech sectors, must adapt their BMs constantly.
Khodaei & Ortt (2019)	Business Model Dynamics reflects not a category of change but a meta-conceptual lens that tracks both the internal evolution and external pressures acting on BMs. - "The highest degree of dynamics requires an entirely novel combination of all BM components and the architecture linking them." - Dynamic capabilities (sensing, seizing, transforming) are foundational to BMD. - Managers must balance current structure with reinvention capabilities
Peñarroya-Farell & Miralles (2021)	Business Model Dynamics refer to the changes occurring in existing firm's business models over time, often in response to an external trigger, can be categorized under the research stream of 'Business Model Dynamics'. Business Model Dynamics focuses on 'how companies change and develop their business models to achieve sustained value creation through time' Different types of BMD have been characterized to represent different levels of strategic changes in firms due to external effects. - BMA, BME and BMI Business Model Dynamics, the evolution and adaptation of business models.

***NOTE: Definitions of BME used in this study are based on prior literature but were carefully adapted to ensure conceptual clarity and empirical usability. We selected only those framings that could be consistently distinguished based on scope and depth of change, while avoiding overlapping or ambiguous formulations that could blur the lines between categories.*

Appendix B – Interview Consent Form Draft

<u>Informed Consent Form</u>

You are being invited to participate in a research study titled " Exploring the Role of Digital Technologies in Business Model Innovation of Renewable Energy Firms in the Netherlands". This study is being conducted by Prithvi Thakkar, a Master's student at TU Delft, Faculty of Technology, Policy and Management, under the supervision of Dr. Hanieh khodaei. This research is part of the graduation thesis for the MSc Management of Technology programme.

The purpose of this study is to identify the key digital technologies being used by high-tech renewable energy firms and to explore how these technologies influence the way these firms create, deliver, and capture value. The interview will take approximately 45 minutes to complete.

You will participate in a semi-structured interview focusing on your firm's use of digital technologies and their impact on your business model over time. Your participation is voluntary, and you may choose not to answer any questions you are uncomfortable with. With your consent, the interview will be recorded and transcribed, after which an anonymous summary will be prepared and shared with you for review. You are welcome to suggest modifications before it becomes publicly accessible as part of the MSc thesis. The collected data may also be reused for future research and educational purposes on technology adoption in renewable energy firms, but all outputs will ensure your anonymity. All personal data will be stored on TU Delft's institutional storage, accessible only to the research team.

As with any online activity, there is a minimal risk of data breach, but we will take all necessary precautions to maintain confidentiality. No personal identifiers, such as names or company names, will be included in the published results. Interview recordings will be securely stored on password-protected university servers, and all data will be anonymized during analysis and used solely for academic purposes. However, due to the niche nature of your work, there remains a small possibility that individuals familiar with the field could infer your identity. All personal data will be deleted at the latest by 30th September 2025.

Your participation is entirely voluntary, and you can withdraw at any time. If you choose to withdraw, you may request the removal of your data within a week after the interview.

By participating in the interview, you acknowledge that you have read and understood this information and agree to participate in the study under the conditions stated above.

If you have any questions about this study or your participation, please contact:

Corresponding Researcher:
Name: Prithvi Thakkar

Responsible Researcher:
Name: Dr. Haineh Khodaei

Signature + Name + Date

Appendix C – Interview Questions Draft

INTERVIEW QUESTIONS
1. Company Background: Q1. Could you walk me through how your company started - what was the original product or service you offered, and who was it intended for? And how has that offering evolved over time into what you provide today? 2. Digital Technology Adoption and Triggers Q2. Could you walk me through the digital technologies your company has adopted over time? 3. Changes in Business Model Components Value Creation Q3. Has the way your company creates value - for example, through your internal processes, product development, or innovation - changed due to implementation of digital technologies? Value Delivery Q4. Have digital technologies changed how you deliver your product or service to customers - such as how they access, use, or interact with your offering? Value Capture Q5. Have there been any changes in how your company captures value; for example, pricing models, revenue streams, or monetization strategies? 4. Business Model Evolution and Innovation Q6. Looking at your company's journey, how would you describe the changes in your business model over time? Have they been small, gradual shifts or major transformations,and have any entirely new business model elements emerged as a result? 5. Future Outlook and Closing Q7. Looking ahead, do you foresee digital technologies continuing to drive further changes in your business model? Are there specific technologies or trends you are keeping an eye on (e.g., digital twins, AI-driven platforms)?

Appendix D – Interview Data Summary (Used for Gioia Mapping)

Interview	Technology Mentioned	Context / Use Case	Observed Effect	BM Component Affected	Quote
Firm A	AI, IoT, dashboards, sensors	Used to optimize industrial site energy procurement, control heating, and manage energy consumption	Improved energy efficiency, cost savings, real-time insights	Value Creation	"They obviously use AI to understand the production processes... They use IoT to control the heating asset on site..."
	Cloud-based dashboards, AI	Dashboards for energy managers, property managers; AI to interpret asset behavior	Informed decision-making, increased control, user engagement	Value Delivery	"They use the dashboard for the property manager to show them what's happened and what is happening under live consumption."
	AI-supported pricing	Flexible pricing based on spot market dynamics, PPA with onsite generation and storage	New revenue streams, pricing agility; Dynamic tariffs, flexible contracts,	Value Capture	"You have a new revenue stream because you can monetize the on-site asset which is not owned by the utility."
	SaaS platforms	Startups providing white-labeled SaaS to utilities or industry clients	Modular service deployment, improved scalability, Partnerships	Value Delivery	"It's a software product for most of the time utility or big corporate offering, oftentimes a

					white label to smaller resellers or customers."
Firb B	IoT, Raspberry Pi, sensors, modebus, mkdd	Smart PV development – real-time monitoring, predictive maintenance, visualisation	Operational efficiency, early fault detection, better data visibility	Value Creation	"IoT like industrial Raspberry, Raspberry Pi and sensors... real time monitoring and visualisation... predictive maintenance purposes."
	Digital Product Passport - Blockchain based	Used for tracking lifecycle data and material traceability	Increased transparency, circularity, customer confidence	Value Creation + Value Delivery	"We are tracking the static datas from the solar panels... metadata as well as other lifecycle datas to trace the module... Digital product passport."
	Open source business model Smart Box	Targeting manufacturers to adopt their circular open-source PV designs	Knowledge diffusion, non-traditional value creation	Value Creation	"We want the manufacturers to adapt our open source... to avoid producing more conventional solar panels."
	Blockchain, Solar Coin (future)	Exploring blockchain for peer-to-peer energy trading and tracking generation rewards	Potential decentralization and incentive alignment	Value Creation + Value Delivery	"Blockchain technologies for sure... peer-to-peer trading... rewards for the people

					who generate energies... solar coin.”
Firm C	IoT (sensors, smart chips)	Embedded in solar panels to collect real-time ground data	Enables real-time, panel-level performance data, Improved traceability, smarter solar assets	Value Creation	“We developed a smart chip that goes on the solar panel... We make the panel smart using IoT sensors like MEMS and SIM cards..." ”
	Blockchain	Used to validate data integrity ; trand & store trusted data records ; enables P2P trading	Increased trust, enables energy trading and performance verification ; additional BM of P2P	Value Delivery + Value Creation	“At the solar panel factory and we're able to use the SIM profile, a bit of cryptography that is blockchain ready to make what is called a digital product passport of the solar panel.” "Solar communities, if you have distributed solar and battery. We can trade energy peer-to-peer. We've acquired a company.."

	AI ; ML	Analyses energy production patterns	Improves predictability and detects pattern	Value Creation	"...our business model is to packetize the that data into different ML and AI data sets and insights."
	API-based Integration + Mobile App/Web Access	External parties (e.g., insurers, grid operators) access verified data	Expands partner ecosystem and monetization options	Value Delivery	"Through our API, insurers and grid operators can plug in to access verified panel performance."
Firm D	Energy Management Systems (EMS) - SaaS	For clients - Control and monitoring of integrated energy systems including solar, battery, EV charging, and heat pumps	Improved energy control, optimized dispatch, peak shaving, grid congestion mitigation	Value Creation + Value Delivery	“Energy management system… controlling and monitoring how energy flows… solar systems as well as batteries, EV chargers, heat pumps…”
	Digital Twin (Simulation Tool)	Simulation of energy scenarios for investment planning and system optimization	Improved investment decisions, better forecasting, pricing justification	Value Creation + Value Delivery	“Let’s now capture all of these things within one platform, creating an energy simulation tool that aims at bringing clarity to the energy transition…”

	Cloud Application Architecture	Remote access, integration with Google Maps APIs, scalable user access	System scalability, ease of use, automation of client workflows	Value Delivery	“It allows portability over different devices… sharing work much easier… automatically estimating how many solar panels…”
	AI	Use of AI tools to accelerate software engineering and reduce overheads	3–4x faster product development, reduced staffing needs, increased responsiveness	Value Creation	“What we built in one year… would have taken 3–4 years before AI… this allowed a small team to achieve market readiness fast.”
Firm E	IoT sensors - Remote Monitoring	Used in modular solar systems to track performance and energy flow	Enables real-time monitoring and predictive maintenance	Value Creation	"The system can be remotely monitored, upgraded, or even shut off if the customer defaults. But more importantly, it provides us a direct feedback loop , we can understand how the product is being used and improve over time.”

	AI for optimization	AI-based analytics on consumption patterns to optimize modular system sizing	Improves personalization and cost-efficiency	Value Creation	"We're looking at how to make the systems more adaptive... personalized in terms of energy management."
	Mobile + Dashboard (UX layer)	Used to give customers visibility and control over energy usage and payments	Enhances customer engagement and trust	Value Delivery	"We use pay-as-you-go solar systems with mobile payments to let people pay in small increments over time."
	Blockchain and Peer-to-Peer (future)	Potential future innovation for energy trading, incentivizing local generation	Unlocks new market mechanisms	Value Creation +Value Capture + Value Delivery	"We're exploring blockchain for peer-to-peer trading. It's early, but could change how value flows in energy systems."

Appendix E – Business Model Change Gioia Mapping

TABLE E. Summary of Business Model Change Types, Themes, Firms, and Representative Quotes

1st-Order Category	2nd-Order Theme	Business Model Change Type	Example Firm(s)	Representative Quote
Local caching for offline operation	Adaptation to infrastructural limitations	Business Model Adaptation (BMA)	Firm E	“In some regions, mobile networks are weak. We’ve had to adapt by building local caching so the system works offline and syncs later when it gets a signal.” (Firm E)
AI-driven onboarding automation	Operational process automation and monitoring	Business Model Evolution (BME)	Firm E	“Earlier we had local sales agents managing onboarding through manual forms… Now, we’ve integrated the credit scoring and onboarding into our app.” (Firm E)
Remote system monitoring and fault diagnosis	Operational process automation and monitoring	Business Model Evolution (BME)	Firm E	“We also monitor the system remotely, so if there’s a technical fault, we can send someone with the right equipment , no more trial-and-error field visits.” (Firm E)
Decision support via scenario comparison	Data-driven decision support and planning	Business Model Evolution (BME)	Firm D	“The platform helps EPCs compare different design scenarios quickly… so instead of gut feeling, they now make data-driven investment decisions.” (Firm D)
Integrated system dashboards and data views	Data-driven decision support and planning	Business Model Evolution (BME)	Firm C	“It was important that we bring together the field hardware, the monitoring dashboards, the installer input, and the owner’s asset view,all in one place.” (Firm C)
AI-enabled product anomaly detection	Data-driven iterative improvement of value creation	Business Model Evolution (BME)	Firm C	“We try to really use AI in a very, very good way to understand what are the abnormalities, what is a trend… we will see a massive drop in battery capacity at what temperature… So really trying to analyze and then design our products accordingly.” (Firm C)
Multi-stakeholder platform integration	Structural expansion of stakeholder engagement	Business Model Evolution (BME)	Firm C	“It was important that we bring together the field hardware, the monitoring dashboards, the installer

1st-Order Category	2nd-Order Theme	Business Model Change Type	Example Firm(s)	Representative Quote
				input, and the owner's asset view,all in one place." (Firm C)
Blockchain-based product traceability and passports	Traceable product identity for circular delivery	Business Model Evolution (BME)	Firm B	"We're using blockchain through a partnership with Circularise to track material provenance and enable product passports. So each panel has a verifiable identity and history , from raw material to assembly to field use. We embed traceability from the start , so when a panel comes back after 10 or 15 years, we know exactly what it contains, where it came from, and whether parts are reusable or recyclable." (Firm B)
Transition from kiosk to pay-as-you-go model	Radical redesign of value logic	Business Model Innovation (BMI)	Firm E	"We started off with the concept… a centralized kiosk system… But we finally figured out… this is not scalable. And then we moved into this pay-as-you-go system… and that has massively scaled up." (Firm E)
Direct asset owner participation in spot markets	New monetization architecture	Business Model Innovation (BMI)	Firm C	"We offer a way that we can get better yield on the solar panel asset… by letting the people play the spot market instead." (Firm C)
Monetization of sensor-generated data streams	New monetization architecture	Business Model Innovation (BMI)	Firm C	"Our proprietary sensor generates high-fidelity field data , and we monetize it multiple times, from insurance analytics to programmable energy to investor dashboards. We don't just sell panels; we build a data economy around them." (Firm C)
Cloud-based simulation platform replacing hardware	Strategic redefinition of value delivery and capture	Business Model Innovation (BMI)	Firm D	"It was mostly hardware-based in the beginning, yes. And that was very difficult to scale. And so, now it's completely cloud-based. We have a software tool that you can use without installing anything. You just log in and start simulating." (Firm D)

Appendix F – SLR Data Summary (Used for Gioia Mapping)

Paper	Digital Technology	Context of Use	Advantages	Limitation	Real-World Case Mentioned
Augello, A., Gallo, P., Sanseverino, E. R., Sciumè, G., & Tornatore, M. (2022). A Coexistence Analysis of Blockchain, SCADA Systems, and OpenADR for Energy Services Provision. IEEE Access, 10, 99088–99101. https://doi.org/10.1109/ACCESS.2022.3205121	IoT, edge devices	IoT/edge tech trigger digital transformation in the power grid.	Enables smarter, responsive, decentralized grid functionality.		
	ICT , communication,	ICT layers are embedded in traditional grid infrastructure.	Real-time visibility and system control; basis for Smart Grids.		
	Blockchain, Machine Learning, Big Data	Demand prediction and automation of DR services.	Intelligent forecasting, system-wide automation, scalable DR.		

	IoT, smart meters	Deployed in SGs for load monitoring, fault management, predictive maintenance, demand forecasting, and distributed asset tracking.	Improves resilience, enables automation, enhances operational visibility, reduces downtime, and supports decentralized generation.		
	IoT (smart meters), Blockchain	IoT has hardware-level and architectural challenges in secure energy applications. Blockchain is introduced as a potential supporting solution.		Limited processing power in smart meters Inability to support asymmetric encryption Decentralization without robustness Poor interoperability Privacy and security vulnerabilities	

	IoT, Blockchain	IoT and SG generate massive data, raising access control issues Decentralization increases cybersecurity risks Blockchain is proposed for energy trading and data tracing among untrusted peers	Blockchain is viewed as a suitable technology for enabling secure transactions and traceability in decentralized energy models.	IoT limitations: hard to enforce access control at scale System-level vulnerability from decentralized architectures Cybersecurity threats: DoS, FDIA, MITM Denial of Service (DoS) False Data Injection Attack (FDIA) Man-in-the-Middle (MITM)	

	SCADA (legacy), Blockchain	Blockchain is positioned as a replacement for SCADA-like centralized systems in smart grids. Used for secure data storage, resilient infrastructure, and decentralized control of complex energy systems.	Resilience to node failure Decentralized trust (no central authority) Secure, tamper-resistant ledger Privacy-preserving and scalable control Supports full decentralization of grid services	SCADA is vulnerable to cyberattacks Single point of failure in centralized models Need for secure sensor data management in distributed environments	

	Blockchain, IoT, SCADA (legacy)	Used jointly to manage and optimize demand-response (DR) programs under high renewable penetration. Blockchain enables secure, transparent coordination of residential energy flexibility in decentralized grids.	Manages load shifting and congestion Reduces GHG emissions Enables residential DR participation Improves system transparency and scalability Provides secure tracking and certification of energy services Encourages low-cost upgrades to SCADA-heavy infrastructure	SCADA still dominates, even where more dynamic platforms (like IoT + blockchain) would be better Interoperability is required for legacy-modern tech coexistence	Reference to BloRin experimental tests validating blockchain use for DR services

Ahmad, T., Zhang, D., Huang, C., Zhang, H., Dai, N., Song, Y., & Chen, H. (2021). Artificial intelligence in sustainable energy industry: Status Quo, challenges and opportunities. Journal of Cleaner Production, 289, 125834. https://doi.org/10.1016/j.jclepro.2021.125834 MORE ENERGY, LESS RE	Artificial Intelligence (AI) - Internet of Things (IoT)	AI is positioned as a technology that supports and enhances energy system modernization. - It complements IoT adoption and renewable integration.	AI helps capture new opportunities from IoT and renewables. - Positioned as a coordination, planning, or optimization enabler.	Current power grids are described as: • Outdated • Inefficient • Unreliable • Lacking fault protection	
	Artificial Intelligence (AI) Machine Learning (ML) Deep Learning (DL) Internet of Things (IoT) Big Data Swarm Intelligence (specifically Particle Swarm Optimization for MPPT) |	AI is applied for smart energy control and forecasting. Used in: PV inverter control, maximum power point tracking (MPPT), energy price and demand forecasting, generation/distribution planning, and system maintenance.	AI increases system efficiency and responsiveness. Enables high-accuracy forecasting and planning. Reduces uncertainty and supports decision-making with benchmark-based performance metrics.	Cybersecurity vulnerabilities grow as AI and IoT adoption increases. Attacks can cause major economic and environmental harm	

	AI adoption limitation			Data issues: Poor quality, missing data, disorganized formats, local storage Infrastructure: Outdated grid systems and legacy equipment Cybersecurity: AI increases digital infrastructure attack surfaces Carbon footprint: AI learning algorithms generate significant CO_2 Lack of expertise: Absence of practical AI skills in both decision-makers and develope	

				rs Economic constraints: High costs of development, configuration, and maintenance Decentralization & complexity: Harder to manage distributed, diverse systems Black box effect: Consumer mistrust due to opacity of AI systems Integration risks: Legacy systems cannot support real-time AI control easily Cellular tech limitations: Reduced access in rural/dev	

				eloping areas Fault diagnosis: Hard to implement AI for fault detection in real-time grid operations Reluctance to experiment: Fear of failure prevents innovation in high-risk sectors like energy	

	AI	AI is positioned as a central driver of innovation across: Business models Energy technologies Energy policy Social innovation Applications mentioned include: Predictive maintenance System sizing Automated contracting Supply chain optimization Load forecasting (short/medium/long-term) Yield optimization in energy production Energy theft detection Automated demand-supply balancing	Improves accuracy of modeling and reliability of decisions Reduces complexity in energy system planning Enables economic dispatch, real-time control, and manual risk elimination Unlocks smarter management of demand-supply dynamics Helps detect theft and minimize losses in vulnerable markets		

Hu, B., Zhou, P., & Zhang, L. P. (2022). A digital business model for accelerating distributed renewable energy expansion in rural China. Applied Energy, 316, 119084. https://doi.org/10.1016/j.apenergy.2022.119084	Digital platforms, remote control tools, IoT	Transformation from PV supplier to integrated service provider across energy and aquaculture sectors	New value streams, cross-sector integration, increased stakeholder participation		TWG
	AI, IV diagnostics, real-time monitoring systems	Use of AI-based tools for improving PV system reliability and minimizing downtime	Enhanced system performance, predictive maintenance, reduced response time		TWG
	Digital platforms (trading, consulting), PV system	Monetization of services through digital platforms alongside traditional power generation	Diversified revenue model, reduced dependence on single output or subsidy		TWG
	Monitoring systems, online trading platforms	Gradual introduction of digital layers to expand value and stakeholder roles	Smooth transformation through layering, resilience via partial digitalization		TWG

	Digital infrastructure, online platforms	Acknowledges social and policy preconditions for successful digital business models		Dependence on external governance, infrastructure, and trust to implement digital transformation	TWG
Del Vecchio, P., Massaro, A., & Garzoni, A. (2025). Circular value creation and business process management for twin transition: The case of an energy company. Computers & Industrial Engineering, 201, 110936. https://doi.org/10.1016/j.cie.2025.110936	ERP, PM software, NAS, CAD servers	Transformation from service-based to product-service circular model	Improved traceability, technical collaboration, KPI measurement		Energy Company
	Excel, ERP, NAS	Digital transition phase involving process redesign using BPMN	Supports gradual adaptation, allows change management		Energy Company
	Sensors, dashboards, anomaly detection	Maintenance and quality assurance in field operations	Operational responsiveness, fault prevention, reduced downtime		Energy Company

	Digital labs, process mapping software, ERP-enabled design	Regional investment with public support to build circular value chain capabilities	Consolidates technical capacity and enables green-digital synergies		Energy Company
Mika, B., & Goudz, A. (2021). Blockchain-technology in the energy industry: Blockchain as a driver of the energy revolution? Energy Reports, 7, 4511–4524. https://doi.org/10.1016/j.egyr.2021.07.028	Blockchain, Smart Contracts	Facilitating peer-to-peer (P2P) electricity trading and disintermediated energy market transactions	Enables decentralization, eliminates intermediaries, and allows prosumers to trade directly		Brooklyn Microgrid (USA)
	Blockchain, Smart Contracts	Automating payments, verifying credit balances, and preventing double sale of energy tokens	Streamlines billing, ensures secure transactions, and reduces operational friction	Complexity of integrating smart contract logic with legacy systems	Token-based pilot programs in EU (e.g., Enerchain, PowerLedger)
	Blockchain, Tokens (EH/EC), IoT	Enabling prosumers to sell generated energy and receive digital tokens for consumption tracking and monetization	Empowers small-scale producers, introduces market access via token incentives, and improves traceability	Token value regulation unclear; needs supporting legal and technical infrastructure	

Muhammad Adnan, Zahid, H., Zulfiqar, A., Sajid Iqbal, M., Shah, A., & Fida, K. (2024). Global Renewable Energy Transition: A Multidisciplinary Analysis of Emerging Computing Technologies, Socio-Economic Impacts, and Policy Imperatives. https://doi.org/10.31224/4112	Cyber-Physical Systems (CPS)	Integration of distributed RE with smart grid systems	Real-time data exchange, simulation, and contingency response	Advanced infrastructure and communication needed	
	Smart Grid / Super Smart Grid	Energy system modernization using DSM, storage, optimization, and IoT	Improves demand-supply control and RE integration	Cybersecurity risks, complexity, infrastructure dependence	
	Digital Twin + Metaverse	Simulating physical assets and testing control strategies	Enables low-risk, high-fidelity optimization and control	Requires massive computing, real-time connectivity	
	AI + Big Data + ML + SVM + ANN	Forecasting, control, predictive maintenance, DR optimization	Automates planning, improves grid efficiency and consumer participation		
	Cloud, Edge, Fog Computing	Data handling, real-time response,	Enhances flexibility, latency control, and		

		sensor integration	service scalability		
	Energy Storage + Digital Tech (IoT, AI, Blockchain, Digital Twins)	Battery and hydrogen storage optimization, anomaly detection, ESS coordination	Improves stability, long-term flexibility, predictive operation		Hydrogen Valley (NL), California Power-to-Gas
	Smart EMS + Optimization Algorithms (GWO, HGS, SSA)	Managing grid reliability, EV integration, and DG placement	Reduces technical losses, increases grid flexibility and protection		Egypt ShC-D8, Siemens MindSphere
Neska, E., & Kowalska-Pyzalska, A. (2022). Conceptual design of energy market topologies for communities and their practical applications in EU: A comparison of three case studies. Renewable and Sustainable Energy Reviews, 169, 112921. https://doi.org/10.1016/j.rser.2022.112921	Aggregator platform + Machine Learning (EcoGrid 2.0)	Forecasting household flexibility potential to balance the grid	Allows optimization of load shifting across prosumers and integration with national grid operations	Low user understanding and system complexity	EcoGrid 2.0 (Denmark)
	Blockchain + Layered Energy System (Hoog Dalem)	Enabling peer-to-peer transactions and local market control through automated	Removes intermediaries, increases transaction trust and transparency		Hoog Dalem 2.0 (Netherlands)

		smart contracts			
	Battery storage + dynamic pricing platform (GridFlex Heeten)	Optimizing energy storage discharge and user load behavior under varying tariff conditions	Enables automated response to price signals and flexible demand alignment	System complexity and limited user scalability	GridFlex Heeten (Netherlands)
	ICT + HEMS + cloud forecasting	Managing household-level energy flows and community-level demand forecasts	Provides individualized feedback and collective optimization		Across multiple EU pilot ECs
Pakulska, T., & Poniatowska-Jaksch, M. (2022). Digitalization in the Renewable Energy Sector—New Market Players. Energies, 15(13), 4714. https://doi.org/10.3390/en15134714	Deep Tech (general)	Used by startups in solar storage (57.9%) and provisioning (65.2%)	Supports energy optimization, embedded software, and component-level control	Concentrated in solar sector; very low in wind and energy providers	
	Software as a Service (SaaS)	Used by 37.5% of solar storage startups; not adopted by wind or energy providers	Enables platform-based, scalable delivery model	Underutilized in most verticals; low integration with connected devices	
	AI, ML, IoT, Big Data	Adopted by ~15% of RE startups overall;	Enables forecasting, real-time control,		

		highest in solar sectors	and user data analytics		
	Commission and Subscription Models	Dominant in solar storage and provisioning; used to monetize energy platforms	Scales with platform use and fosters recurring revenue streams		
Plewnia, F. (2019). The Energy System and the Sharing Economy: Interfaces and Overlaps and What to Learn from Them. Energies, 12(3), Article 3. https://doi.org/10.3390/en12030339	Digital Platforms	Enable peer-to-peer trading, virtual storage, and community coordination	Facilitate decentralized control, non-utility participation, and local value exchange		
	Smart Meters and Transparency Tools	Enable energy usage visibility and peer accountability in community energy settings	Supports trust, monitoring, and incentive alignment within local groups		
	Crowdfunding and Cloud-based Energy Pools	Allow community members to jointly finance and access RE infrastructure	Unlocks new capital sources and user ownership structures		
	Blockchain and Trust Protocols	Proposed for future C2C or community governance coordination	Could enhance traceability, automate trust, and		

			remove intermediaries		
Rasagam, G., & Zhu, D. (2018). Delivering on the Promise of Distributed Renewable Energy Entrepreneurship in Sub-Saharan Africa. Current Sustainable/Renewable Energy Reports, 5(4), 230–239. https://doi.org/10.1007/s40518-018-0120-x	PAYG Mobile Platforms + Smart Metering	Enable remote credit-based access to solar energy and appliances	Supports affordability, real-time control, and customer engagement	Relies on GSM coverage; local repair ecosystems underdeveloped	M-Kopa,
	Cloud-based Monitoring and Analytics	Used for asset diagnostics, predictive maintenance, and customer behavior tracking	Improves service quality, lowers downtime, supports credit risk analytics		Mobisol monitoring platform
	Mobile Microfinance + PAYG APIs	Support recurring payments and credit scoring via mobile money integrations	Builds credit history, expands financial inclusion, de-risks customer acquisition		Integration of PAYG API in telecom-DRE partnerships
	Integrated DC Systems + Appliance Bundling	Bundling energy kits with DC TVs, lights, fans, and irrigation devices	Increases perceived value, supports multi-service delivery	High initial capital cost; product-specific constraints on scalability	BBOXX, M-Kopa bundled kits

Bartczak, K. (2021). Digital Technology Platforms as an Innovative Tool for the Implementation of Renewable Energy Sources. Energies, 14(23), 7877. https://doi.org/10.3390/en14237877	Digital Technology Platforms (DTPs)	Used for managing RES systems, customer interaction, energy trading, and personalization	Modular, extensible, supports service automation, user configuration, and prosumer participation	Cybersecurity threats, data protection concerns, long payback periods, and weather dependence	Platforms in Poland managing PV and wind farms; crowdfunding and monitoring functions integrated
	DTPs with Crowdfunding and Crowdsourcing Functions	Enable financing and idea sourcing directly from users through platform interfaces	Broadens capital access, deepens community engagement, supports co-investment in RES		RES platforms in rural and eastern regions of Poland
	Algorithmic Personalization Tools within DTPs	Automate selection and purchasing decisions based on user preferences and energy data	Improves service responsiveness, customer satisfaction, and operational efficiency		Platform configurators for RES sizing and usage forecasting
Bartczak, K., & Łobejko, S. (2022). The Implementation Environment for a Digital Technology Platform of Renewable Energy Sources. Energies, 15(16), Article 16. https://doi.org/10.3390/en15165793	Digital Technology Platforms (DTPs)	Coordinate stakeholder interactions and manage RES systems through modular services	Support user participation, modular upgrades, and cost-effective automation	Cybersecurity threats, system failures, user hesitancy due to technical risks	

	Blockchain-Integrated DTPs	Enable peer-to-peer energy trading and transaction transparency without brokers	Reduces costs, increases trust, and automates energy exchange processes		
	Open-Source DTPs with Customizable Modules	Support continuous development of services and tools for energy companies and users	Drives innovation, enables personalization, and builds multi-level relationships with customers		
D'Amore, G., Di Vaio, A., Balsalobre-Lorente, D., & Boccia, F. (2022). Artificial Intelligence in the Water–Energy–Food Model: A Holistic Approach towards Sustainable Development Goals. Sustainability, 14(2), Article 2. https://doi.org/10.3390/su14020867	AI + Digital Twins	Real-time simulation of asset performance and predictive decision-making in energy and water systems	Reduces cost and downtime, improves forecasting accuracy and operational sustainability	Energy consumption, device waste, and cybersecurity vulnerabilities	Applied in water-energy-agriculture nexus systems for offsite monitoring and scenario analysis
	AI-enabled IoT + Remote Sensing	Used for weather prediction, grid monitoring, demand forecasting, and	Supports decentralized control, improves system responsiveness,	Reliant on data connectivity and sensor reliability	

		decentralized energy delivery	reduces manual intervention		
	AI + Big Data for Decision Support	Used for scenario analysis, SDG alignment, and sustainability-oriented decision-making	Enhances data-driven planning, resilience, and accuracy; avoids bias from human judgment	Cyber threats, requires training and new governance models	AI models applied to optimize water-energy-food interactions at system level
Franki, V., Majnarić, D., & Višković, A. (2023). A Comprehensive Review of Artificial Intelligence (AI) Companies in the Power Sector. Energies, 16(3), Article 3. https://doi.org/10.3390/en16031077	AI Forecasting and Demand Prediction Tools	Applied to solar, wind, and demand-side forecasting for grid optimization	Improves prediction accuracy, enhances system flexibility, reduces reliance on backup capacity	Requires integration of weather and sensor data; risk of model errors or poor training	
	Virtual Power Plants (VPPs) and AI System Optimization	Used to coordinate distributed resources, optimize dispatch, manage flexibility and market risks	Enables decentralized system operation and automation of complex power flows	Complex integration of diverse DERs, interoperability and control challenges	
	AI-Based Predictive Maintenance and O&M Robotics	Used for smart grid and RES equipment diagnostics, including drone and satellite data analysis	Reduces downtime, increases equipment life, lowers inspection costs	Upfront costs, data reliability, and need for integration with hardwar	

				e interface	
	AI-Powered Customer Relationship Management (CRM)	Used to unlock meter-level data, personalize engagement, and automate customer interaction	Increases customer satisfaction, allows value-based segmentation, supports service-based models	Low current adoption in utilities; transition from commodity to service still lagging	
Gitelman, L., & Kozhevnikov, M. (2023). New Business Models in the Energy Sector in the Context of Revolutionary Transformations. Sustainability, 15(4), Article 4. https://doi.org/10.3390/su15043604	Virtual Power Plants (VPPs)	Aggregate DERs to balance supply/demand, provide flexibility, and support real-time grid services	Enables bidirectional flows, decentralized participation, and real-time optimization	Requires digital coordination, interoperable systems, and regulatory maturity	LimeJump in UK balancing market using big data and machine learning
	Blockchain + Smart Contracts	Enable P2P energy trading between users connected via secure platforms	Reduces transaction costs, increases transparency, enables secure automation	Normative and administrative barriers to adoption	Ethereum-based solar trading pilot in New York
	Energy-as-a-Service (EaaS) Platforms	Offer bundled services for infrastructure management, energy efficiency,	Revenue from recurring service, not energy volume; aligns with	Requires advanced analytics and ecosystem of partners	Microenvironment control and energy storage optimization services in

		and usage optimization	consumer comfort and performance		EaaS contracts
	Smart Grid + Analytics Platforms	Monitor, forecast, and optimize energy flows and asset life cycles	Improves infrastructure reliability, enables predictive maintenance, and extends asset life	Requires significant investment and cybersecurity protections	
K. N., A. S. I., S., M., Desai, K., S., H. K., & Kautish, S. (2024). Optimizing Green Power and Green Energy Through Digital Technologies. In W. Leal Filho, S. Kautish, T. Wall, S. Rewhorn, & S. K. Paul (Eds.), Digital Technologies to Implement the UN Sustainable Development Goals (pp. 275–304). Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-68427-2_14	Digital Twins	Used to create virtual replicas of renewable energy systems for real-time monitoring and predictive maintenance	Enables efficient resource use, predictive fault detection, optimized system operations	Dependent on real-time data quality and integration capabilities	
	Smart Grids + IoT + Sensors	Used for integrating distributed renewable sources, balancing demand, and enabling responsive grid behavior	Supports grid stability, demand-side flexibility, and decentralized control	Requires robust communication and data security systems	

	Energy-as-a-Service (EaaS) Models	Offers subscription-based clean energy services tailored to user performance and sustainability needs	Avoids infrastructure costs, provides outcome-based value, promotes clean energy adoption	Depends on real-time data collection and advanced analytics infrastructure	
	Peer-to-Peer (P2P) Trading Platforms + Blockchain	Enables secure energy transactions among prosumers and consumers in local microgrids	Promotes decentralization, user empowerment, transparent energy exchange	Regulatory and administrative limitations to widespread deployment	
Leiva Vilaplana, J. A., Yang, G., Monaco, R., Bergaentzlé, C., Ackom, E., & Morais, H. (2025). Digital versus grid investments in electricity distribution grids: Informed decision-making through system dynamics. Applied Energy, 386, 125536. https://doi.org/10.1016/j.apenergy.2025.125536	Smart Meters	Record real-time energy consumption and enable communication between customers and the grid	Reduces technical and commercial losses; supports outage reduction and demand response	Requires robust communication and integration systems	Portuguese DSO case: widespread smart meter roll-out reduced O&M and failure duration
	Substation Automation	Automates control and monitoring of substations for higher reliability and	Reduces failure probability, enables predictive maintenance,	Upfront CAPEX in automation infrastructure and O&M	Automation of Portuguese substations according to

		operational efficiency	improves grid stability		IEC61850 standard
	AI-based Process Automation	Handles repetitive administrative and operational tasks across DSO infrastructure	Increases data processing speed and reduces manual error	Requires skilled personnel and continuous OPEX support	Portuguese DSOs used AI to automate form filling, calculations, and diagnostics
	Data Analytics	Analyzes grid data to detect anomalies, reduce failures, and support forecasting	Improves performance metrics, enables condition-based maintenance and fault prediction	Depends on algorithm quality and real-time data infrastructure	Portuguese DSOs implemented analytics to reduce outage frequency and maintenance costs
Liu, J., Huang, Z., Fan, M., Yang, J., Xiao, J., & Wang, Y. (2022). Future energy infrastructure, energy platform and energy storage. Nano Energy, 104, 107915. https://doi.org/10.1016/j.nanoen.2022.107915	Smart Grids	Distributed energy system upgrades	Fast system response and improved reliability	Aging infrastructure; Unpredictable disruptions	-
	Energy Platforms	Digital ecosystem integrating producers, consumers, storage	Enables ecosystem-level interaction and control	Complex interplay of data, signals, energy; underdeveloped sector	-

	Blockchain	Peer-to-peer energy trading	Secure, decentralized transaction layer	High implementation and security complexity	-
	Sensors, Digital Twins	Monitoring and controlling bidirectional energy and data flow	Real-time optimization and control	Technical complexity and need for interoperability	-
	Cloud Computing	Coordinated, distributed control of energy networks	Flexibility and system-wide optimization	High computing demands	-
	AI & Big Data Analytics	Managing system complexity in power-electronics-heavy grid	Handles massive device coordination and complexity	Requires high computational power and advanced models	-
	Subscription / Bundled Services	Service-based value models in energy platforms	Monetizes through service diversity and personalization	Requires robust infrastructure and control layers	-

Malewska, K., Cyfert, S., Chwiłkowska-Kubala, A., Mierzejewska, K., & Szumowski, W. (2024). The missing link between digital transformation and business model innovation in energy SMEs: The role of digital organisational culture. Energy Policy, 192, 114254. https://doi.org/10.1016/j.enpol.2024.114254	General Digital Transformation (DT)	Sector-wide modernization of processes and models	Enables long-term growth, new business models	Cultural resistance; slow adoption in energy SMEs	-
	IoT	Grid monitoring, communication, demand forecasting	Enhances security and enables smart services	Slower pace of adoption in upstream operations	-
	AI	Analytics for production optimization and infrastructure monitoring	Improves decision-making and predictive capabilities	High analytical complexity	-
	Platform Technologies	Enabling new product/service offerings and collaboration models	Drives new interactions and product logic	SME difficulty in capability reconfiguration	-
	Organizational Culture	Alignment with DT goals and technology adoption	Influences success of BMI	Mindset resistance and lack of digital leadership	-

Singh, M., Jiao, J., Klobasa, M., & Frietsch, R. (2021). Making Energy-transition headway: A Data driven assessment of German energy startups. Sustainable Energy Technologies and Assessments, 47, 101322. https://doi.org/10.1016/j.seta.2021.101322	AI, IoT, Big Data	Customer segmentation, pricing, forecasting, maintenance	Automation, personalization, operational efficiency	Startups must build data-sharing ecosystems	German startups
	Blockchain (DLT)	Peer-to-peer trading, billing, supplier switching	Removes intermediaries, increases transparency	Immaturity; security and trust challenges	German startups
	Digital Twin	Infrastructure monitoring and automation	Real-time control, performance optimization		German startups
	Platform Technologies / XaaS	Energy trading, electric mobility, prosumer platforms	Multi-sided value creation; customer engagement	Immature models; dependency risks	German startups
	Cloud & Digital Services	Grid coordination, pricing, flexibility-as-a-service	Interoperability; enables modular service layers	Requires partner collaboration and customer trust	German startups
	Digital Infrastructure (General)	Energy management, smart homes, storage, grid simulation	Supports diverse applications across sectors		German startups

Bähr, K., & Fliaster, A. (2023). The twofold transition: Framing digital innovations and incumbents' value propositions for sustainability. Business Strategy and the Environment, 32(2), 920–935. https://doi.org/10.1002/bse.3082	Virtual Power Plants (VPPs)	Aggregation and control of decentralized generation units	Enables access to energy markets; balances RES volatility	Outcomes depend on framing: may limit to efficiency or enable sustainability	
	AI, Cloud, Big Data	Embedded in VPPs to manage distributed assets	Automation, forecasting, load dispatch	Requires strong digital infrastructure and framing alignment	
	Legacy Platforms	Use of VPPs for internal operations	Cost-saving, process optimization	No external stakeholder value; no sustainability focus	
Ciano, M. P., Peron, M., Panza, L., & Pozzi, R. (2025). Industry 4.0 technologies in support of circular Economy: A 10R-based integration framework. Computers & Industrial Engineering, 201, 110867. https://doi.org/10.1016/j.cie.2025.110867	Digital Twin	Process energy modeling, predictive decision-making, energy efficiency optimization	Improves energy efficiency, reduces waste, and optimizes resource utilization		

	Simulation / Optimization Models	Scenario planning, analyzing energy consumption, reducing emissions	Supports optimal decision-making for emissions and energy planning		
	Cognitive Twins	Decision support for sustainable energy strategies and long-term competitiveness	Supports sustainable decision-making and competitive energy advantage		
	Big Data Analytics (BDA)	Optimizing freight logistics to reduce emissions and enable personalization	Enables lower-emission logistics and personalized energy-related services		
Skaloumpakas, P., Sarmas, E., Rachmanidis, M., & Marinakis, V. (2024). Reshaping the energy landscape of Crete through renewable energy valleys. Scientific Reports, 14(1), 8038. https://doi.org/10.1038/s41598-024-57471-7	Power Systems Digital Twin (PSDT)	Real-time monitoring, scenario simulation, and optimization of decentralized local energy grids	Improves energy efficiency, system reliability, fault prevention, and autonomy	Lack of mature tools for scalable replication of digital twin coordination	Crete REV-Lab with 4 CELs (Arvi, Lasithi, Arkalochori, Atherinolakkos)

	Semantic Interoperability Framework	Data exchange between decentralized energy systems, enabling P2P trading and grid services	Enables smart grid coordination and seamless communication between community systems and market layers		Crete REV-Lab
	Artificial Intelligence (AI) Forecasting	Predictive load modeling, storage optimization, consumer behavior segmentation	Increases grid efficiency and improves energy planning; enables personalized incentives		Crete REV-Lab
	REV Decision Support Tool (DST)	Stakeholder-facing GIS-integrated interface for infrastructure planning, scenario evaluation, and CEL participation	Supports social acceptance, transparency, and multi-actor coordination	Limited tool availability and weak user awareness across community projects	Crete REV-Lab
	Optimized Scheduling + Transfer Learning	Flexible energy management, behavior modeling, battery optimization across CELs	Reduces cost, improves system flexibility, and increases storage efficiency		Crete REV-Lab

Sułek, A., & Borowski, P. F. (2024). Business Models on the Energy Market in the Era of a Low-Emission Economy. Energies, 17(13), Article 13. https://doi.org/10.3390/en17133235	Internet of Things (IoT)	Used for monitoring and intelligent control of energy consumption and system status in distributed generation	Enables real-time tracking and automation of consumption patterns, improving energy efficiency		
	Artificial Intelligence (AI)	AI used in energy platforms to automate analysis, optimize grid operations, and forecast energy demand	Improves decision-making accuracy, reduces losses, enhances system performance		
	Energy Platforms	Digital platforms integrating producers, distributors, and consumers for transparent energy exchange	Enables flexible energy trading, decentralized coordination, and consumer participation		
	Blockchain	Used within digital platforms for secure, transparent energy transactions and smart contracts	Improves trust, reduces intermediaries, enables tamper-proof P2P energy exchange		

	Energy-as-a-Service (EaaS)	Energy companies offer services (e.g., consumption optimization, RES, storage) instead of kWh units	Improves energy efficiency, shifts focus from commodity to service, enables long-term engagement		
Venkatachary, S. K., Prasad, J., & Samikannu, R. (2017). Challenges, Opportunities and Profitability in Virtual Power Plant Business Models in Sub Saharan Africa—Botswana. International Journal of Energy Economics and Policy, 7(4), Article 4.	Virtual Power Plants (VPP)	Coordination of distributed energy resources (DERs), enabling grid optimization and decentralized control	Allows for scalable, efficient, and resilient grid operations with prosumer participation	Lack of interoperability, high capital costs, low trust and awareness among prosumers	Botswana (sub-Saharan Africa context)
	Smart Grids	Infrastructure layer enabling two-way communication, demand response, outage management, and market access	Enables prosumer interaction, improves system stability, supports renewable integration	High investment costs, cybersecurity vulnerabilities, lack of standardization	Botswana
	Advanced Metering Infrastructure (AMI)	Automated metering and data collection from end-users and prosumers in a digital grid	Improves energy usage visibility, billing accuracy, and load management	Data manipulation risk, cyberattacks, lack of data governance in	

				Botswana	
	Demand Response (DR) Systems	Shifting or reducing electricity usage during peak hours to balance load and market signals	Reduces peak demand, lowers grid stress, enables market-based consumer engagement	Requires active consumer participation, behavior change, and infrastructure readiness	Botswana and US-based DRMS evolution
Vom Scheidt, F., & Staudt, P. (2024). A data-driven Recommendation Tool for Sustainable Utility Service Bundles. Applied Energy, 353, 122137. https://doi.org/10.1016/j.apenergy.2023.122137	Machine Learning (XGB, ANN)	Recommendation of cost-minimal energy service bundles combining tariffs and leased sustainable tech (EV, HP, PV, battery)	Enables personalized bundles, high customer savings, platformization of utility services	May misclassify edge cases, performs poorly on rarely observed bundles, user trust risk	292 households in London, UK (Low Carbon London project)
	Smart Home Energy Optimization System	Optimizes operation of EVs, heat pumps, PV, and batteries under different tariffs to identify lowest-cost bundle	Captures technology interaction, reveals synergies between flexible tariffs and sustainable tech	Assumes perfect foresight, neglects manual demand response, simplifies user behavior	292 households in London, UK

	Automated Demand Response (ADR)	Enables shifting of flexible load (EV charging, heat pump usage, storage) based on price signals	Enhances customer savings, increases value of time-varying tariffs, aligns demand with supply	Relies on automation; excludes behavioral flexibility and manual DR potential	Simulated in London-based energy bundles with and without automation
Zhao, Y., Xia, S., Zhang, J., Hu, Y., & Wu, M. (2021). Effect of the Digital Transformation of Power System on Renewable Energy Utilization in China. IEEE Access, 9, 96201–96209. https://doi.org/10.1109/access.2021.3094317	Short-Term Renewable Energy Output Prediction	Forecasting next-day power output for wind and solar stations using environmental and historical data	Improves dispatch planning, enhances integration of variable renewables, increases prediction accuracy	Forecast quality depends on data availability and accuracy (e.g., weather, output records)	Northwest China (regional grid and RE stations, 2012,Äì2019)
	Digital Maintenance Guidance for RE Equipment	Real-time monitoring and predictive maintenance of wind/solar station assets using data platforms and inspection systems	Reduces fault restoration time, improves availability, enhances service reliability	Requires integrated platform deployment and quality meteorological + sensor data	Northwest China RE power stations
	Intelligent Power Grid Maintenance	Fault monitoring and predictive grid maintenance using digital analysis platforms	Improves grid stability, reduces downtime, supports high-RE penetration	Dependent on sensor coverage, operator responsiveness, and grid data quality	State grid operation in Northwest China

Appendix G – Use of AI Assistance

During the course of writing this thesis, I used OpenAI's ChatGPT as a support tool to assist with various academic writing tasks. Specifically, ChatGPT was used to:

- Refine the structure and clarity of my writing.
- Suggest improvements to grammar and phrasing.
- Validate ideas and interpretations as I developed my arguments (e.g., asking whether a line of reasoning made sense or aligned with existing literature).
- Provide critical review and second-opinion feedback on sections I had already written.
- Help clarify complex concepts when I was stuck or unsure about how best to express something.

All core research, analysis, and final writing decisions were conducted and made by me. ChatGPT served as a helpful companion in the process offering feedback, not authorship. This acknowledgment is provided in the interest of transparency and responsible use of AI tools in academic work.