systems

MDPI

Systematic Review

Digital Technologies as Drivers of Business Model Change in the Renewable Energy Firms: A Systematic Literature Review

Prithvi Thakkar *, Hanieh Khodaei *, J. Roland Ortt and Ghassan Kharbeet

Faculty of Technology, Policy & Management, Delft University of Technology, 2628 BX Delft, The Netherlands; j.r.ortt@tudelft.nl (J.R.O.); g.kharbeet@tudelft.nl (G.K.)
* Correspondence: prithvi.thakker@onerooftech.com (P.T.); h.khodaei@tudelft.nl (H.K.)

Abstract

Digitalization is increasingly reshaping business models, yet the mechanisms through which specific digital technologies influence business model transformation in renewable energy remain insufficiently understood. Unlike prior research that treats digitalization and business models separately or focuses on macro-level impacts, this study examines how digital technologies affect business model components—value creation, value delivery, and value capture—in renewable energy firms and the extent to which they drive business model adaptation, evolution, or innovation. It aims to combine insights from the literature on digitalization, sustainability, and business models. Through a systematic literature review following the four-phase PRISMA methodology, 32 peer-reviewed studies were analyzed using a combination of descriptive, bibliometric, and Gioia-based thematic coding analyses to identify structures and patterns across the dataset. The analysis introduces a functional grouping perspective, linking digital technologies to business model components, and business model changes. Findings reveal that the same technology can enable multiple, overlapping transformation pathways and that outcomes vary depending on how technologies are implemented and embedded within firm operations. This study contributes theoretically by integrating a functional technology lens and sustainability lens with business model change typologies—a novel integrative framework absent from the prior literature. It practically provides a framework to help renewable energy firms move toward sustainability-oriented reconfiguration of business models by prioritizing and integrating digital tools effectively, thereby enhancing competitive advantage and accelerating value capture from digitalization. This paper closes with directions for future research on technology-enabled business model change.

Keywords: digital technologies; business model components; business model change; renewable energy; systematic literature review; sustainability and digitalization

Academic Editor: Agostinho Da Silva

Received: 27 December 2025
Revised: 12 February 2026
Accepted: 24 February 2026
Published: 3 March 2026

1. Introduction

The global transition toward renewable energy is accelerating in response to intensify climate goals. Within this shift, renewable energy firms, particularly those operating in innovation-driven contexts, face a complex landscape of rapid technological innovation, regulatory complexity, and the urgent need for business model (BM) flexibility. Unlike traditional utilities, they must continuously adapt their value propositions, delivery channels, and revenue mechanisms in response to policy shifts and technological opportunities. These firms are increasingly adopting digital technologies to transform not only their operations but also their strategic positioning [1–3]. Technologies such as artificial intelligence (AI), the

Internet of Things (IoT), blockchain, digital twins, and cloud platforms are enabling predictive forecasting, remote control, platform-based services, and consumer-centric design, for example. These digital tools are not just enhancing technical performance but also creating new opportunities for firms to reconfigure how they create, deliver, and capture value [4–6]. This makes the sector an ideal setting for understanding how digital technologies catalyze BM transformation.

Despite the growing attention to digitalization in the energy sector, much of the existing literature has focused on macro-level impacts such as grid flexibility, market decentralization, and technology integration [7–9]. Few studies have systematically examined the firm-level consequences of digital technologies, specifically, how they influence the architecture and evolution of BMs and especially in renewable energy companies [2,10–16]. While some empirical research has demonstrated the potential of digital technology platforms to facilitate innovative business models and intensify stakeholder relationships in the energy sector [17], broader analyses indicate that actual implementation remains fragmented. For instance, recent evidence shows that many renewable energy startups still struggle to fully integrate digital business models, often relying on traditional value delivery methods rather than realizing deep digital transformation [18]. These gaps are especially evident in studies examining how digitalization acts as a catalyst for structural changes within BM components and value logic [14,15].

To address this gap, our study builds a three-layered conceptual framework. The first layer focuses on digital technologies as transformation triggers. There is little prior research on understanding the triggers of BMs in sustainability-oriented companies, which has been recognized as an important research gap to be addressed [19,20]. Existing research often treats digital transformation and BM and sustainability as separate domains, highlighting the need for integrative frameworks to holistically capture their interplay [21,22].

These include technologies that enable real-time data exchange, remote monitoring, decentralized market participation, and automation of system functions, ranging from AI and machine learning to blockchain and energy-specific digital platforms [4,10,23,24].

The second layer examines BM components, which are defined as value creation (how offerings are produced or co-produced), value delivery (how offerings reach users and through which infrastructure), and value capture (how value is monetized and sustained) [25]. This gap relates to the understanding of the integrative mechanisms of value logic transition when modelling a business through the lens of sustainability [26]. This structure draws on the established literature that conceptualizes BMs as the configuration of value creation, delivery, and capture mechanisms, forming a vital link between firm strategy and market implementation [25,27–29].

We also read these mechanisms through a sustainability lens [30], linking digital roles to efficiency, resilience and inclusion outcomes relevant to energy transitions [31]. This approach helps us to investigate how synergies between digitalization and sustainability unfold.

The third gap concerns the outcomes of BM change to beyond established links to firm performance through novel value configurations in the BM [28,32–34]. So, the degree of BM change can be related to business model adaptation (BMA), business model evolution' (BME) and, to 'business model innovation' (BMI). BMA refers to incremental and reactive adjustments made in response to environmental changes or competitive pressure [35,36]. BME describes continuous but coherent shifts in model structure that maintain internal alignment and competitiveness over [37–39]. Finally, BMI entails more radical reconfigurations that introduce new value logics, revenue mechanisms, or platform-based structures [28,35,40]. So, the degree of change is increasing from 'business model adaptation' (BMA) to 'business model evolution' (BME) to 'business model innovation'

(BMI). BM changes then leads to a sequence of BM changes in form of BMA, BME or BMI changes over time.

Using this conceptual framing, this study preset how digital technologies act as enablers of BM change in renewable energy firms. The focus is on high-tech and digitally embedded firms, those developing or applying smart, data-driven energy solutions, rather than traditional utilities. These firms often operate in complex, regulated, and data-rich environments where BM flexibility is key to competitiveness [3,41]. However, the strategic implications of their digitalization efforts remain fragmented across academic literature.

To synthesize these insights, we conduct a systematic review that combines descriptive and bibliometric analyses with Gioia-style thematic coding to surface first-order concepts, second-order themes, and aggregate dimensions, and to map how digital technologies related to BM elements changes and typology of changes [42].

The study is guided by the following main research question: How do digital technologies drive changes in business models for renewable energy firms?

For clarity, this review focuses on renewable energy firms, those developing solar, wind, hydro, geothermal, and biomass technologies, which represent a subset of the broader sustainable energy sector.

This question shapes the design and analytical focus of the review, which seeks to uncover how digital technologies influence the architecture, components, and transformation pathways of BMs in this context.

This review contributes to academic theory by linking specific digital technology to sustainability-oriented reconfiguration in BM elements and type. From a practical standpoint, this study offers insights into how renewable energy firms can move from isolated tool adoption toward digitally coherent business strategies. At the same time, this study also recognizes that integrating digital technologies in this sector involves several limitations related to data quality, cybersecurity, interoperability, and institutional complexity, which are discussed later in this paper.

By organizing and interpreting fragmented insights into a unified analytical framework, this study enhances our understanding of how digital technologies serve as catalysts of BM transformation in the renewable energy sector. It also provides a foundation for future empirical research on digital strategy and innovation in sustainable energy systems.

The remainder of this paper is organized into four chapters: Section 2 describes the research design and methodology, outlining the systematic literature review process, and the application of the Gioia methodology. Section 3 presents the findings across three analytical layers: functional roles of digital technologies, their influence on BM components, and the types of BM change they enable. Section 4 discusses these findings in greater depth, highlighting patterns across technology groups, BM elements, and transformation trajectories, while also addressing limitations and synthesizing insights. Finally, Section 5 concludes the paper by summarizing the key contributions, offering theoretical and practical implications, and proposing directions for future research.

2. Research Design and Methodology

This study uses a systematic literature review (SLR) to investigate how digital technologies influence business model (BM) change in the renewable energy sector. The review is grounded in a structured conceptual model that connects three dimensions: key digital technologies, BM components (value creation, value delivery, value capture), and types of BM change (BMA, BME, and BMI).

Following established review protocols [43], the process involves three core phases: planning the review and selecting sources, conducting the analysis through data extraction and coding, and presenting descriptive and thematic findings. The Gioia methodology [42] is adapted to organize and interpret qualitative data from selected studies, allowing for inductive theorization grounded in the reviewed literature.

2.1. Research Question Formulation

The research questions guiding this study are informed by a clear gap in the literature at the intersection of digital transformation and BM change within renewable energy firms [3]. While digitalization is widely discussed in technical and sectoral contexts, their influence on how firms create, deliver, and capture value is rarely touched upon [44]. Existing studies often focus on operational efficiencies or infrastructure optimization but seldom examine how these technologies drive reconfigurations in BM logic or strategic positioning [41].

To address this gap, this review is guided by the following main research question: how do digital technologies drive changes in business models for renewable energy firms?

To capture the different facets of this phenomenon, the primary question was supported by three sub-questions: (1) What are the key digital technologies influencing business models in renewable energy firms? (2) What are the mechanisms through which digital technologies shape the components of business models, including value creation, value delivery, and value capture? (3) What types of business model changes are triggered by digital technologies in renewable energy firms?

These questions structure the entire review process and inform the search strategy, inclusion criteria, and coding dimensions used in the following stages.

2.2. Planning the Review: Search and Filtering

The literature review process was designed using principles from systematic review methodology to ensure transparency, replicability, and analytical rigor [43]. The Scopus database was selected as the primary source due to its broad interdisciplinary coverage and inclusion of high-quality peer-reviewed journals in energy, management, and information systems [45,46]. The search was conducted in April 2025 and targeted articles published between 2015 and 2025 to reflect developments over the last decade, a period during which digitalization has become increasingly central to renewable energy strategy and BMs.

The search string was constructed to capture the intersection of three key dimensions: digital technologies, business models, and the renewable energy sector. The Boolean query used was as follows:

("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").

This string was designed to retrieve articles discussing digital transformation tools in the context of business model structure or innovation within renewable energy settings. The search was limited to English-language, peer-reviewed journal articles and excluded conference proceedings, editorials, and gray literature to ensure methodological rigor and editorial transparency [43]; however, this choice may underrepresent perspectives from non-Anglophone regions (such as China) with significant renewable energy innovation and limits access to emerging practices documented in industry reports or conference proceedings.

Initial screening was conducted based on titles and abstracts, followed by full-text reviews for inclusion. Articles were included if they (1) explicitly examined the use or application of digital technologies in the context of renewable or sustainable energy; (2) provided insights into changes related to BM components, BM transformation, or firm-level strategic reconfiguration; and (3) focused on renewable energy contexts or electricity systems with clear sustainability relevance. Articles were excluded if they were

https://doi.org/10.3390/systems14030269

purely technical (e.g., focused solely on optimization algorithms and device control systems) without any substantive connection to BM considerations or digital transformation.

After applying these criteria and removing duplicates, the final sample consisted of 32 peer-reviewed journal articles. The review process followed PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines [47] to ensure methodological transparency. The completed PRISMA checklist is provided as Supplementary Materials (Table S1). The four-phase PRISMA flow diagram [Figure 1] outlines the identification, screening, eligibility, and inclusion steps used in the review.

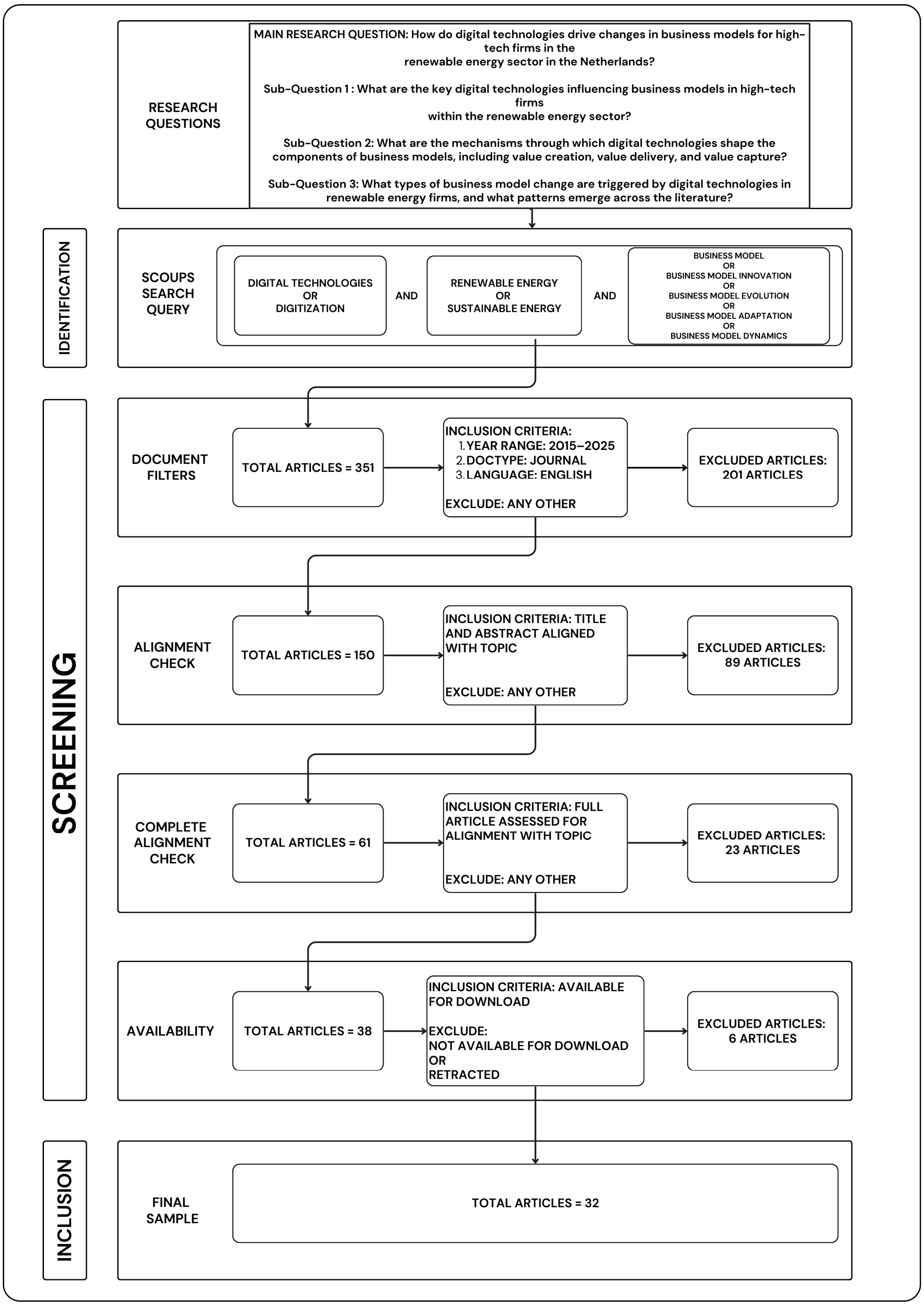

Figure 1. SLR PRISMA Flow Diagram.

This planning phase laid the foundation for structured data extraction and thematic synthesis in the subsequent stages of the review.

2.3. Conducting the Review: Extraction, Analysis, and Synthesis

Once the final set of 32 articles was selected, the analysis phase began with systematic data extraction and inductive coding. To structure the analysis and generate theory from the literature, this study adopted the Gioia methodology, a qualitative research approach that supports inductive concept development through rigorous coding and abstraction [42,48,49]. The methodology has been effectively applied in structured literature reviews where the aim is to uncover recurring concepts, build second-order themes, and connect them to overarching theoretical dimensions [50].

Each article was read in full and manually coded. Relevant content was extracted into structured tables, focusing on passages that addressed digital technologies, BM components, or types of BM change. The extraction process retained contextual clarity by using the exact or closely paraphrased language from the articles. These excerpts formed the basis of the first-order concepts, capturing author-reported phenomena such as the role of AI in predictive maintenance or the use of digital platforms for energy-as-a-service delivery.

As the first analytical layer, digital technologies were coded to uncover the functional roles they played in enabling BM change. This process resulted in the Gioia Tree of Technological Triggers, which organized relevant first-order concepts into second-order themes that reflect recurring digital functions observed across the dataset. These themes capture how technologies such as artificial intelligence, the Internet of Things, blockchain, digital twins, and cloud-based platforms contribute to shifts in firm behaviour, decision-making, infrastructure coordination, and customer interaction. This analysis forms the basis of the study by highlighting the mechanisms through which digital technologies influence BM transformation in renewable energy firms. So, rather than directly connecting the adoption of digital technologies to BM changes, we decided to take the mechanism of change into account by clarifying the function of these digital technologies and then their effect (through their function) on BM components.

In addition to this first layer of analysis, separate coding structures were applied to analyze how these technologies influenced BM components and types of change. While some first-order concepts appeared across more than one coding lens, the extraction and grouping processes were independently carried out for each Gioia tree to reflect the specific analytical dimension. BM components were coded under value creation, value delivery, and value capture [25,28]. Types of BM change were classified as adaptation (BMA), evolution (BME), or innovation (BMI), drawing from established typologies of BM transformation [35,38].

To maintain analytical traceability, the Gioia structure was applied consistently across all articles. Each quote or insight was linked to a specific BM component and assigned a corresponding change type where applicable. This ensured that the synthesis did not rely solely on researcher interpretation but remained anchored in the language and logic of the source materials. The coding process was iterative, with themes refined as patterns emerged across the dataset. In cases where a paper addressed multiple technologies or intersecting BM elements, multiple coding was allowed. To ensure coding quality and validity, the initial coding was reviewed by the 2 co-authors who assessed the consistency of theme assignment, the appropriateness of aggregations, and the alignment of second-order themes with the source material. Throughout this review process, discrepancies in interpretation were resolved through iterative discussion and consensus, where conflicting coding decisions were revisited against the source text and the Gioia coding framework until agreement was reached. For instance, articles describing how smart meters and substations support predictive fault detection and delivery optimization were initially coded as operational efficiency improvements. Upon secondary review, the co-authors recognized these as BME rather than adaptation, as the technologies reshape multiple value creation and delivery mechanisms while maintaining core utility-centric value logic.

Through consensus discussion referencing typology criteria, the team confirmed this represents the "Operational Evolution through Intelligent Automation and Infrastructure Digitization" pattern, where there is multiple-component reconfiguration without systemic institutional disruption. This validation process ensured that the final Gioia trees reflected shared understanding of patterns across the dataset and enhanced synthesis reliability. This iterative peer-review validation aligns with established criteria for trustworthiness in qualitative research [51] and serves as a member checking mechanism [52] that enhances the credibility of the Gioia coding outcomes.

The Gioia-based synthesis enabled a rich, layered understanding of how digital technologies shape BMs in renewable energy firms. It revealed both the diversity of digital applications and the varied strategic responses they enable. This structured analysis laid the groundwork for presenting the findings as three interconnected Gioia trees in the next chapter: one each for (1) digital technology triggers, (2) business model components, and (3) types of business model change.

2.4. Descriptive and Bibliometric Findings

To contextualize the selected literature and understand the evolution of scholarly attention to the topic, a bibliometric overview was conducted based on the final sample of 32 peer-reviewed articles. This descriptive analysis complements the thematic synthesis by offering a macro-level view of the research field's development over time and across disciplinary domains.

The year-wise distribution of publications [Figure 2] reveals a clear upward trend in scholarly interest at the intersection of digital technologies, BMs, and renewable energy. Beginning with isolated papers in 2015–2017, the volume of publications steadily increases after 2018, with a notable surge in the period between 2020 and 2024. This trend aligns with broader developments in energy system digitalization and the growing pressure on firms to innovate BMs in response to policy, market, and climate imperatives [4,12].

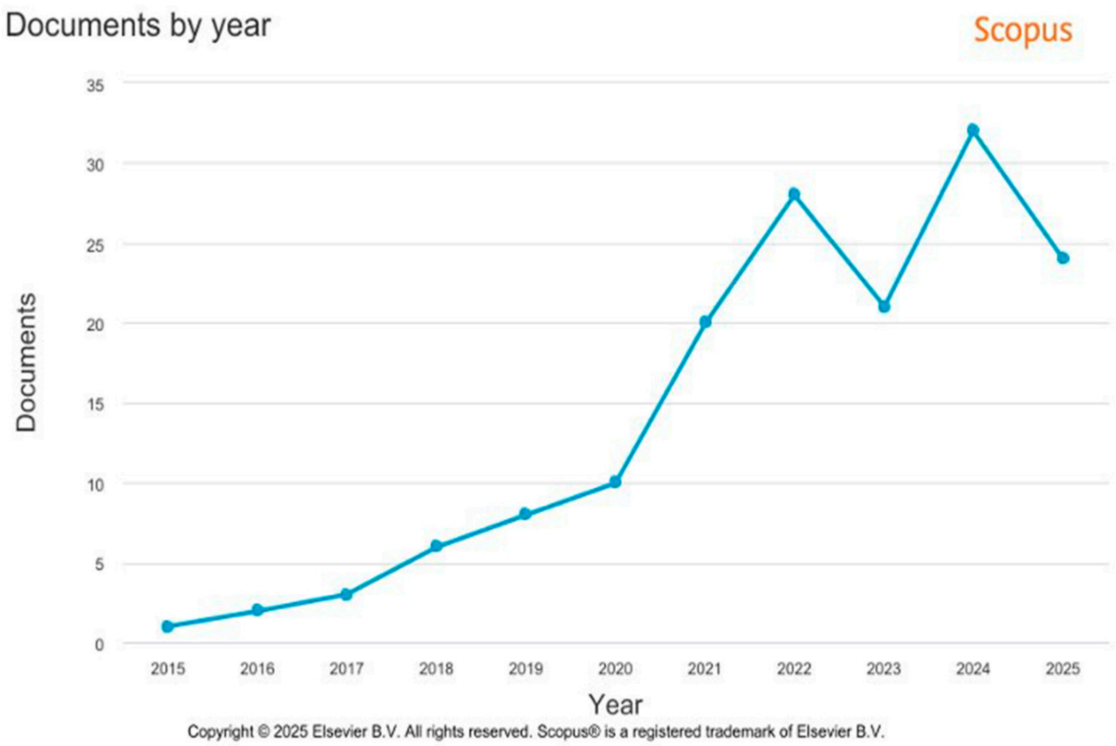

Figure 2. Year-wise distribution of peer-reviewed journal articles included in the SLR (2015–2025).

Citation analysis of the sample identifies three highly influential contributions: reference [7] on AI in the Water–Energy–Food nexus (86 citations), reference [23] on blockchain as an energy revolution driver (48 citations), and reference [10] on digital business models for rural renewable energy (46 citations). Keyword analysis reveals three core clusters: (i) digital technologies ("AI," "blockchain," "digital transformation," and "Industry 4.0"), (ii) business model concepts ("business model innovation," "digital business model," and "business models"), and (iii) energy/sustainability themes ("renewable energy," "energy transition," "circular economy," and "prosumer").

A disciplinary breakdown of the article sample [Figure 3] confirms the multidisciplinary nature of this research stream. Articles are drawn from journals in energy systems, sustainability science, innovation management, and digital transformation. Categorization by subject area (as indexed in Scopus) shows a near-even distribution among energy and environmental sciences, engineering and technology, and business and management. This reflects the integrative challenge of the topic, which cuts across technological, business strategy, and market design.

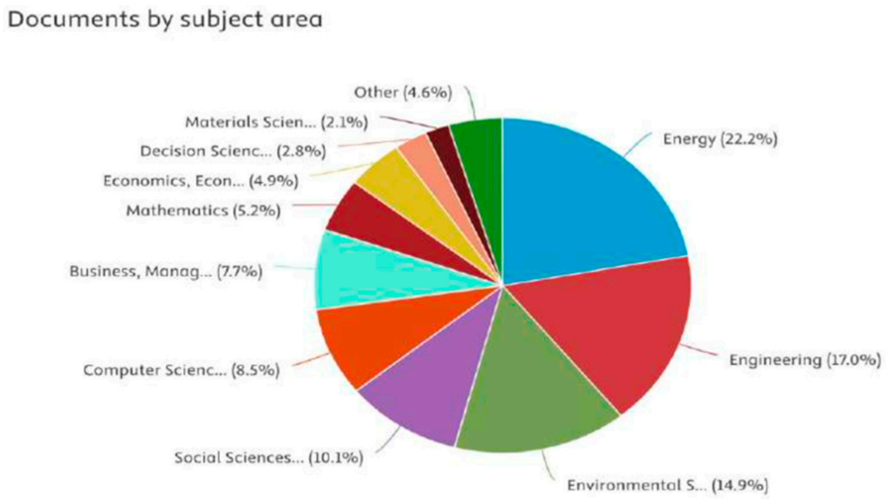

Figure 3. Subject Area Distribution.

These findings underscore the novelty and relevance of the chosen research focus. While interest in digital technologies in energy is well-established, the literature that links these technologies to strategic BM transformation is still emerging. The diversity of publication outlets and the recent growth in volume suggest that this domain is in a formative stage, marked by conceptual experimentation, dispersed case studies, and limited cross-study generalization. This further validates the need for a structured synthesis such as the one presented in this review.

3. Findings/Results

This chapter presents the findings of the systematic literature review, based on a qualitative coding process guided by the Gioia methodology. The analysis addresses the central research question, which explores how digital technologies influence business model (BM) change in renewable energy firms. The results are organized across three analytical layers, each aligned with one of the sub-questions. These layers include the role of digital technologies as triggers of transformation, the mechanisms through which they affect BM components, and the types of change they bring about. Each layer is presented using a separate Gioia Tree, consisting of first-order concepts, second-order themes, and aggregate dimensions. The sections that follow summarize the key themes and patterns observed across the dataset.

3.1. Key Digital Technologies and Their Functional Roles

The first layer of analysis focuses on identifying the key digital technologies that appear across the selected literature and understanding the roles they play within renewable energy firms. Rather than listing technologies in isolation, the review organizes them into functional clusters that reflect how they are used in practice. These clusters were derived inductively through the coding process and capture common digital capabilities such as data capture, system intelligence, and decentralized coordination. The resulting Gioia Tree [Figure 4] groups individual technologies into second-order themes based on their observed functions in business contexts. This structure serves as the foundation for the remaining analysis by clarifying the technological landscape that underpins BM change in the sector.

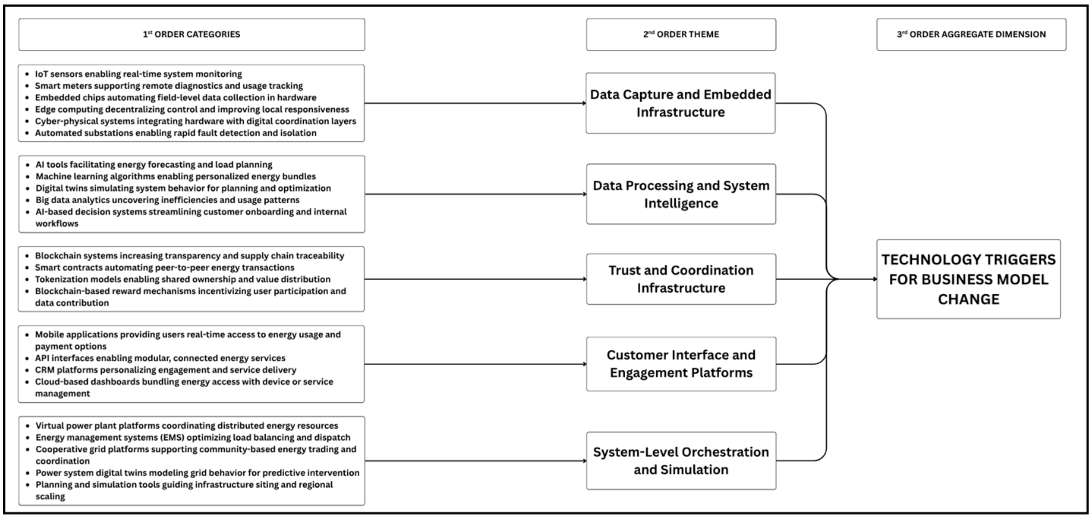

Figure 4. Functional Grouping of Digital Technologies as Triggers for Business Model Change.

3.1.1. Data Capture and Embedded Infrastructure

Widespread use of Internet of Things (IoT) devices, embedded sensors, and remote monitoring systems across renewable energy applications reflects a common shift toward real-time, data-rich operations [4,53]. In distributed solar setups, for example, sensors track generation performance, fault conditions, and weather fluctuations to allow for faster diagnosis and maintenance. Smart meters and networked controllers enable utility and energy service providers to capture granular consumption data, which forms the foundation for predictive system optimization and load balancing. Across the literature, these technologies serve as the infrastructural layer that links physical energy systems with digital decision-making environments. They are frequently implemented at the edge of operations, embedded within devices or installations, and are essential for enabling more automated, responsive, and data-informed business processes [54–56].

3.1.2. Data Processing and System Intelligence

As firms in the renewable energy sector accumulate more real-time and historical data, there is a growing reliance on tools that can process this information into actionable insights. Applications of artificial intelligence and machine learning appear frequently across the literature, particularly in areas such as predictive maintenance, demand forecasting, and performance optimization [3,4,8]. These technologies allow firms to move beyond descriptive monitoring toward anticipatory and autonomous decision-making. In several cases, rule-based analytics are replaced by adaptive models that improve over time as more operational data becomes available [4,7,8]. This shift is visible not only in core energy generation and distribution functions, but also in supporting activities like asset lifecycle management or consumer demand profiling. Such capabilities enable more agile, intelligent operations and provide the analytical foundation for more complex service offerings and pricing models [57].

3.1.3. Trust and Coordination Infrastructure

Several papers emphasize the growing importance of technologies that support coordination among distributed actors and ensure trust in data integrity, system access, and transactional interactions. Blockchain appears as a prominent enabler in this space, particularly for functions such as peer-to-peer energy trading, asset traceability, and contract automation. Its decentralized structure helps reduce dependency on centralized intermediaries, making it attractive for new energy markets and collaborative value chains [5,23]. In parallel, API-based integrations and interoperability standards play a foundational role in allowing different systems and platforms to work together effectively [17,55,58]. These technologies do not necessarily produce or analyze data on their own but serve as the connective layer that secures, validates, and synchronizes activities across the energy ecosystem. Their role becomes particularly crucial in multi-party arrangements where transparency, auditability, and coordination must be maintained across organizational boundaries [23,53].

3.1.4. Customer Interface and Engagement Platforms

A distinct group of technologies focuses on enabling more interactive, personalized, and user-centric energy services. Digital platforms, mobile applications, and web-based dashboards are commonly deployed to improve how firms engage with end users, whether residential consumers or commercial clients. These tools allow customers to monitor their energy usage in real time, adjust preferences, receive alerts, or access bundled service offerings [17,59]. In some cases, platforms support on-demand features such as remote diagnostics or dynamic pricing feedback, reinforcing the shift toward greater customer involvement in energy management [4,54]. Firms increasingly use these interfaces not just for communication but also for service differentiation and value co-creation [18,24]. The literature points to a broader trend of integrating front-end digital experiences into the core of energy BMs, reflecting how digitalization is reshaping firm–customer relationships beyond traditional utility interactions.

3.1.5. System-Level Orchestration and Simulation

Several studies highlight the use of digital tools that support system-wide modeling, scenario analysis, and dynamic configuration of energy solutions. Technologies such as digital twins, simulation platforms, and cloud-based optimization engines are increasingly used to test and design energy systems before physical deployment [4,11,54]. These tools enable firms to evaluate different configurations of solar panels, storage units, grid inputs, or user behaviors under various conditions, allowing for more accurate planning and investment decisions [4,55,58]. In some cases, firms use these capabilities to offer configurator-based services, where customers can visualize or simulate their own energy setups in real time [17]. By modeling interdependencies and forecasting outcomes, these technologies play a strategic role in aligning technical feasibility with business objectives, especially in contexts with high uncertainty or regulatory complexity.

3.2. Business Model Components

The second layer of analysis examines how digital technologies influence individual components of BMs in renewable energy firms. Drawing from the BM literature, these components are structured as value creation, value delivery, and value capture. Rather than treating these elements as isolated activities, the analysis explores how digital tools interact with and reshape the resources, activities, partnerships, channels, and revenue mechanisms that make up these components. The second-order themes discussed in this section reflect recurring mechanisms observed across the reviewed literature, showing how digitalization affects the way firms generate, deliver, and sustain value. These relationships are summarized in the Gioia-based coding structure of business model components shown in Figure 5.

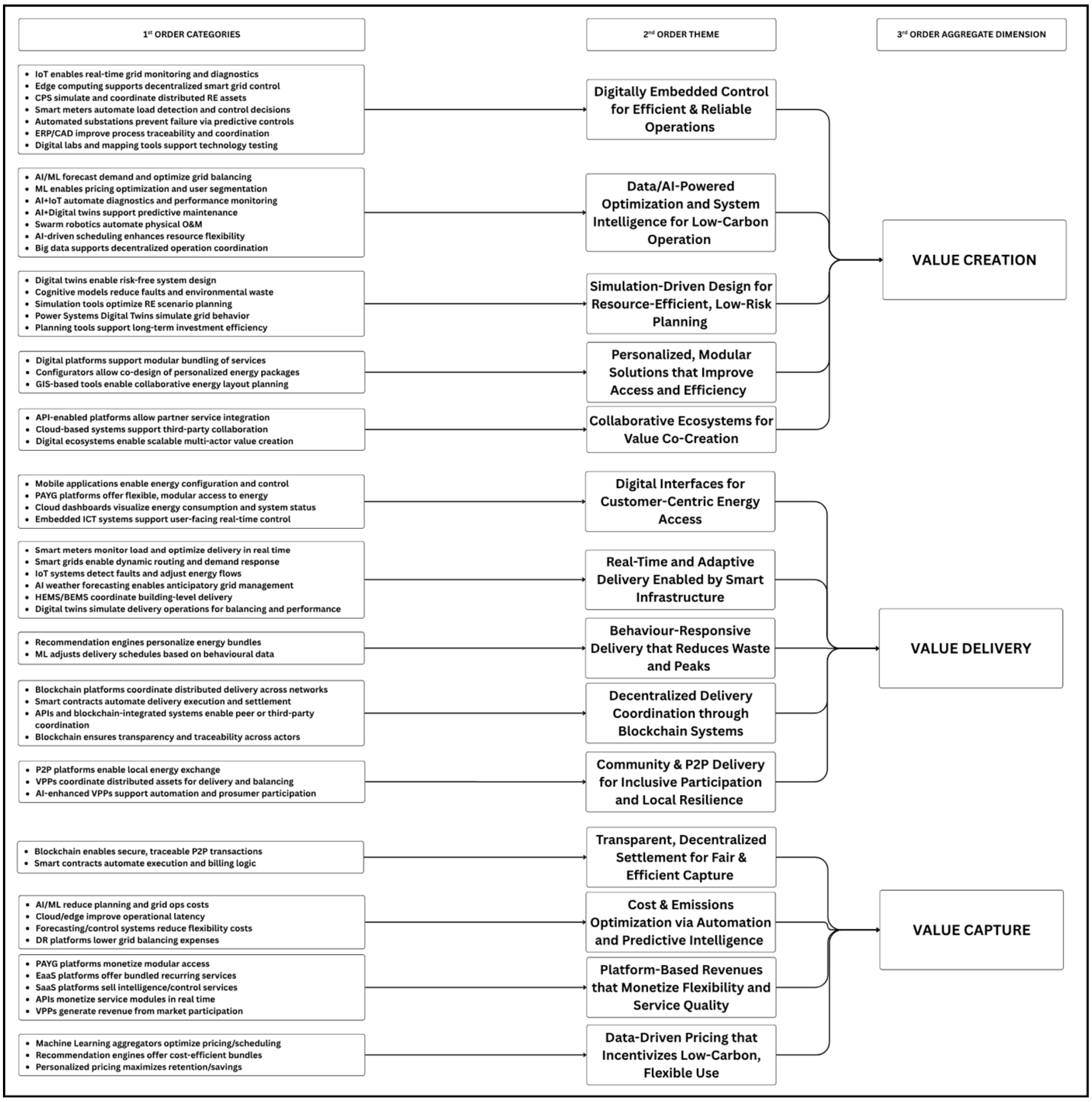

Figure 5. Gioia Coding Structure of Business Model Components.

3.2.1. Value Creation

Digital technologies have redefined how renewable energy firms create value by transforming physical systems into intelligent, adaptive infrastructures. At the core of this shift is the integration of IoT sensors, smart meters, and cyber–physical systems, enabling real-time monitoring, automated diagnostics, and responsive control across decentralized assets [4,6,55]. These digitally embedded infrastructures allow firms to improve efficiency, reduce downtime, and extract value not only from energy production but also from data flows. Edge computing supports this by enabling low-latency decision-making near the data source, while ERP systems improve traceability and process alignment across operations [4,12]. Building on this foundation, artificial intelligence (AI), machine learning (ML), and big data analytics embed system intelligence within operations, supporting accurate forecasting, predictive maintenance, and load optimization [4,13,55,57,60]. These tools enhance responsiveness while enabling firms to anticipate and adapt to fluctuating energy demands. Simulation platforms, especially AI-powered digital twins, allow firms to test configurations, monitor asset behavior virtually, and make infrastructure decisions with lower risk and higher long-term efficiency [7,11,53,58]. These tools also support personalized energy planning at the regional and community levels [61]. Digital configurators, modular platforms, and CRM tools allow energy firms to unbundle and repackage services based on consumption profiles and geographic needs [8,10,17]. This modularity enables flexible bundling, customer participation, and localized infrastructure alignment. Finally, the emergence of collaborative ecosystems driven by cloud platforms and platform cooperativism allows firms to co-create value with partners and users through shared infrastructures and interoperable services [4,10,13,62]. Collectively, these capabilities mark a transition toward flexible, intelligent, and networked value creation strategies in the renewable energy sector.

3.2.2. Value Delivery

Digital technologies are transforming value delivery in renewable energy firms by enhancing transparency, responsiveness, and decentralization. Mobile-based platforms and embedded ICT systems play a foundational role in making energy services more accessible, particularly in underserved regions. Firms like M-Kopa use GSM-enabled Pay-As-You-Go (PAYG) systems to allow users to activate and pay for energy on flexible terms, while cloud dashboards and mobile apps enhance customer engagement and energy literacy [1,5,9,12,61]. These user interfaces improve service visibility and foster participation, especially when paired with embedded ICT systems that enable remote monitoring, load control, and interactive feedback [13,17,18,56]. At the infrastructure level, smart meters and IoT-enabled devices create a responsive energy delivery network by detecting faults and adjusting supply in real time [6,9,54,63]. These are complemented by AI-powered forecasting tools that predict load fluctuations and optimize delivery schedules across distributed systems [7,8,17,55,59]. Smart grid applications, including Home and Building Energy Management Systems (HEMS/BEMS), allow for real-time coordination and demand-based adaptation at the building level [57,59]. Digital twins further enhance this adaptability by simulating energy flows and optimizing dispatch across infrastructure layers [7,11–13,53,55]. On the personalization front, AI-driven platforms enable firms to tailor delivery based on behavioural data, creating individualized service bundles and adaptive delivery patterns [11,13,24,57]. At the system level, blockchain-based delivery systems support decentralized coordination and transparent, contract-based automation of services across actors [5,6,17,56]. Peer-to-peer (P2P) energy sharing and Virtual Power Plants (VPPs) offer participatory delivery structures where prosumers contribute to grid balance through digitally coordinated exchanges [1,5,23,56,58]. AI tools further automate asset dispatch and optimize localized delivery operations [1,8]. Altogether, these digital innovations enable delivery models that are not only more efficient and real-time but also more participatory, personalized, and system-integrated.

3.2.3. Value Capture

Digital technologies are reshaping value capture in renewable energy firms by introducing decentralized, automated, and data-driven monetization models. Blockchain and smart contracts form the foundation for peer-to-peer transaction environments by enabling secure, auditable exchanges and automating billing processes [5,6,23,59]. These tools support traceability in energy flows, codify prosumer rules, and reduce administrative overhead [13,53,54]. Alongside this, digital forecasting, automation engines, and demand response platforms optimize operational costs and infrastructure planning. AI and ML reduce forecasting errors and downtime, while cloud and edge computing enable faster, localized decision-making [6–8,55,57]. Flexible revenue models such as Pay-As-You-Go, Energy-as-a-Service, and Software-as-a-Service, enable recurring monetization while lowering user entry barriers. These platforms support real-time bundling and modularity through open APIs and platform integration [1,5,18,44,53,61,64]. AI-powered platforms also apply granular pricing logic and behavioural segmentation to align user value with consumption and flexibility potential. ML-based engines and big data analytics are used to create personalized energy–tariff bundles and forecast supply–demand trends, enhancing price responsiveness and customer retention [8,17,54,55,57]. In sum, these technologies move value capture from fixed, transactional models toward flexible, intelligent systems that monetize not just electricity but also data, participation, and digital services.

3.3. Types of Business Model Change

The final layer of analysis investigates the types of business model change enabled by digital technologies in renewable energy firms. This section applies the previously introduced typology of business model change, distinguishing between adaptation (BMA), evolution (BME), and innovation (BMI). These categories were defined earlier in the Introduction and are used here to organize the observed change trajectories across the selected studies. Using the Gioia coding structure, reviewed articles were examined for how digital technologies contributed to each of these change types. The resulting Gioia Tree [Figure 6] highlights conceptual clusters that connect digital mechanisms to the strategic nature of business model transformation, offering insights into the pace, scope, and intent of change across different organizational contexts.

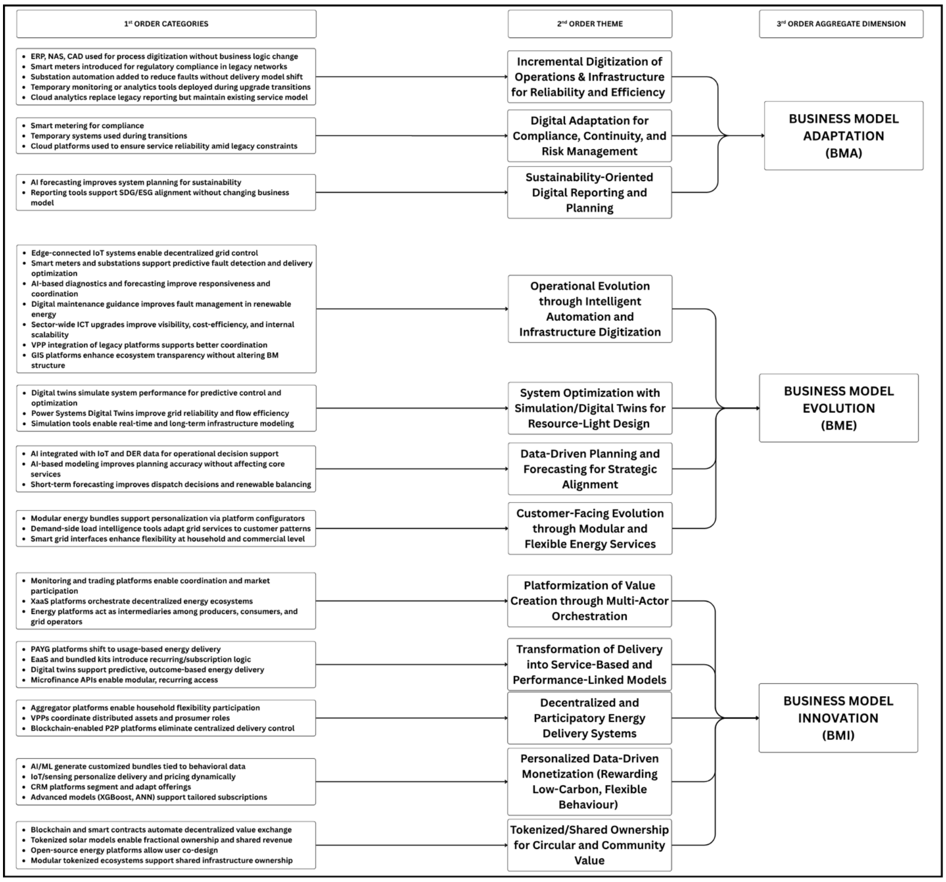

Figure 6. Gioia Coding Structure of Business Model Change Types.

3.3.1. Business Model Adaptation

BMA in the renewable energy sector is characterized by incremental, internally focused changes that improve operational efficiency or align with policy goals without altering the fundamental BM structure. Many firms adopt digital technologies to upgrade infrastructure, automate internal systems, and enhance planning accuracy. For instance, substation automation [63] and ERP/NAS integration [12] improve fault detection, coordination, and performance tracking but leave service delivery and customer models unchanged. Similarly, AI-driven scenario modelling and cognitive digital twins support sustainability reporting and alignment with SDGs [8,11], yet these tools primarily serve compliance and planning purposes. Across the literature, such digital interventions reinforce existing workflows and strategic logic, marking them as adaptive rather than transformative.

3.3.2. Business Model Evolution

BME in renewable energy firms is marked by digital upgrades that improve performance, coordination, and responsiveness while maintaining the core value logic. A key pattern is the operational evolution enabled by intelligent automation and decentralized infrastructure, with IoT, edge computing, and smart meters improving load management and fault detection across grid systems [6,56,63]. Forecasting engines and AI diagnostics further support planning and real-time responsiveness without altering value propositions [8,61,63]. Simulation and digital twin technologies are widely used for predictive maintenance and performance optimization in distributed environments, enhancing system intelligence without modifying delivery models [11,55,58]. Data-driven planning and forecasting tools are also adopted to align operations with strategic goals and manage uncertainty while preserving the monetization logic [4,8,55,64]. Finally, customer-facing services are evolving through modular platforms, EMS systems, and adaptive control enabled by cloud and IoT systems, offering greater service flexibility without redefining revenue or delivery structures [9,11,55]. These developments collectively illustrate a digital evolution of how firms function while the BM architecture remains fundamentally intact.

3.3.3. Business Model Innovation

These innovations often emerge through iterative, trial-and-error processes where firms experiment with platform designs and revenue models, learning from failures and scaling successes [65]. BMI in the renewable energy sector is increasingly driven by digital platforms, intelligent systems, and decentralized control architectures that fundamentally reshape how value is created, delivered, and captured. Platformization enables multi-actor orchestration across producers, prosumers, and service providers, shifting firms from centralized providers to ecosystem enablers [10,13,18,56,61]. This is complemented by the rise in service-based and performance-linked models such as Pay-As-You-Go (PAYG) and Energy-as-a-Service (EaaS), which bundle generation, monitoring, and financing into recurring offerings, replacing one-time transactions with ongoing delivery logic [5,7,53,61]. Decentralized delivery structures enabled by Virtual Power Plants (VPPs), AI, and blockchain, further allow prosumers to participate in real-time coordination and grid services, creating participatory energy ecosystems [1,23,59,64]. Simultaneously, AI, ML, and CRM analytics are enabling personalized monetization via behavioural segmentation, dynamic pricing, and modular service bundling tailored to individual users [6,8,17,57]. Finally, tokenized ownership and open-source platforms introduce radically new governance and value-sharing structures, empowering users to co-own, co-design, and co-monetize energy services through smart contracts and distributed ledgers [5,23,24,47]. Together, these innovations reflect a systemic shift in BM logic—from centralized, asset-heavy approaches to dynamic, participatory, and digitally mediated ecosystems.

4. Synthesis

Understanding the historical development of business model research provides the context for interpreting contemporary digital-driven transformations [66]. Modern business models are increasingly characterized by digital embeddedness, ecosystem participation, and value co-creation with multiple actors—patterns that distinguish contemporary models from earlier conceptions. This chapter integrates the review's findings into a single narrative that connects (i) the functional roles of digital technologies, (ii) their effects on business model (BM) components (value creation, delivery, and capture) through a sustainability lens, and (iii) the types of business-model change they precipitate (adaptation, evolution, and innovation). Rather than treating these strands separately, we read them together: foundational functions create operational visibility; higher-order capabilities build on that base; and, as interactions deepen across components and partners, change accumulates and can reconfigure the underlying logic. Sections 4.1–4.3 therefore present one story through three lenses.

4.1. Key Digital Technologies and Functional Groups

The review reveals a wide array of digital technologies shaping renewable energy BMs. To analyse their impact systematically, these technologies are grouped into functional categories based on how they operate within energy systems. This functional lens allows us to move beyond individual technologies and observe the patterns through which they enable BM change. Another reason to form functional groups of technologies is that many different digital technologies exist and new ones will emerge over time, a limited number of functional groups will thus create overview. Finally, digital technologies can be used in different ways in companies and thus induce completely different BM changes. By grouping technologies in functional groups, the effect on BMs is clearer. Digital technologies can be part of multiple functional groups, depending on their specific application in companies. For example, digital twins function as Simulation and Planning when used in pre-deployment testing, but shift to Monitoring and Control when linked to live operational data, and to Forecasting and Optimization when generating dispatch recommendations. AI similarly spans groups: demand forecasting places it in Forecasting and Optimization, anomaly detection in Monitoring and Control, and customer personalization in User Interfaces. In this study, we assign each technology to its primary functional group based on its most direct BM impact, while acknowledging these secondary roles. Although the empirical sample for this review is bounded to studies published between 2015 and 2025, the functional taxonomy is designed to accommodate emerging digital tools. For instance, early applications of generative AI for automated scenario generation, report drafting, and conversational planning assistants would primarily fall under Data Processing and System Intelligence, where they support forecasting, option exploration, and decision support, while secondary uses in personalized advice or chatbot-based guidance would place them within Customer Interface and Engagement Platforms. Likewise, high-bandwidth, low-latency communication standards such as 5G primarily expand the reach of Data Capture and Embedded Infrastructure and System-Level Orchestration and Simulation by enabling denser sensor deployments and near real-time control of distributed assets. These examples illustrate that emerging technologies can be classified by their dominant functional roles rather than by adding new categories, preserving the framework's adaptability as the digital energy landscape evolves.

The key functional groups are:

- Data Capture and Embedded Infrastructure for Monitoring and Control: Technologies such as IoT sensors, edge computing, and cyber-physical systems that collect and

https://doi.org/10.3390/systems14030269

process real-time data. These tools form the operational backbone for adaptive control, fault detection, and decentralized decision-making.

- Data Processing and System Intelligence for Forecasting and Optimization Engines: AI, ML, and digital twins used for demand prediction, dispatch planning, and operational optimization. These tools introduce intelligence, enable predictive maintenance, and reduce costs.
- Customer Interface and Engagement Platforms: Mobile apps, cloud dashboards, CRM systems, and configurators that facilitate interaction between users and the energy system. These interfaces improve accessibility, personalization, and user participation.
- Trust and Coordination Infrastructure: Blockchain, smart contracts, and virtual power plant (VPP) platforms that manage distributed energy coordination. These tools decentralize control, automate transactions, and support peer-to-peer delivery.
- System-Level Orchestration and Simulation/Planning Tools: Digital twin models, scenario simulators, and planning interfaces that guide infrastructure design and long-term decision-making. These tools enable experimentation, improve resilience, and align systems with sustainability goals.

Taken together, these roles are cumulative: instrumented, data-rich operations enable predictive and planning tools; shared standards and verifiable records make distributed coordination and user-facing interfaces viable; and, in more advanced settings, simulation and orchestration support system-level redesign. We use these roles not as rigid boxes but as triggers that firms can layer and recombine.

This functional taxonomy approach is theoretically grounded in the dynamic capabilities perspective [67], which emphasizes that technology value emerges not from the tools themselves but from how firms orchestrate and integrate them into strategic processes. Further, it aligns with discovery-driven approaches to business model understanding [68], which recognize that business model development is an iterative learning process where firms discover viable configurations through experimentation. Thus, rather than categorizing technologies by type, organizing them by function reveals the strategic logic through which digital tools enable business model transformation. By grouping technologies into five functional categories, we clarify how their contributions map to BM components and the types of change they enable. The next section analyses this in greater detail.

4.2. Business Model Components Value Reconfiguration

The reconfiguration of value creation, delivery, and capture mechanisms through digital technologies has direct implications for organizational sustainability [69]. Digital technologies reconfigure value creation, value delivery, and value capture by activating distinct functional groups: monitoring and control, forecasting and optimization, simulation and planning, user interfaces, and coordination and exchange.

4.2.1. Value Creation

Monitoring and control systems (IoT, smart meters, CPS, ERP) elevate situational awareness and coordination across distributed assets, enabling proactive performance management and efficiency gains [12,63]. Forecasting and optimization engines (AI, ML, big data) support predictive control, dynamic load balancing, and intelligent scheduling, thereby reducing operational uncertainty and improving resource utilization [4,8,55]. Simulation environments and digital twins enable ex-ante testing and design optimization, lowering cost and risk, while interface tools such as CRMs, AI configurators, and modular bundling platforms extend value creation through personalization and co-creation with users [17,57]. In short, value creation is dominated by monitoring/control and forecasting/optimization, with simulation amplifying design quality and interfaces opening demand-side co-production where propositions are configurable. Collectively, these shifts underpin resource efficiency and emissions avoidance at asset and portfolio levels.

4.2.2. Value Delivery

Interfaces coupled with smart infrastructure (PAYG platforms, cloud dashboards, and embedded EMS) bridge physical systems and end users, improving accessibility and transparency, particularly in off-grid contexts [55,61]. Forecasting and optimization tools (AI-based load and weather prediction; HEMS/BEMS) enable real-time, decentralized coordination that supersedes static scheduling [8,9]. Coordination and exchange infrastructures, notably blockchain and VPPs, facilitate peer-to-peer trading, prosumer aggregation, and community balancing, positioning users as active agents in delivery [1,5,23,59]. Thus, delivery shifts most when interfaces externalize control and feedback and when coordination infrastructures reassign roles; forecasting amplifies both by improving timeliness and reliability. Decentralised coordination and transparent interfaces enhance reliability and energy equity, particularly in underserved contexts.

4.2.3. Value Capture

Forecasting and optimization improve planning precision and operational efficiency, reducing downtime and overcapacity and strengthening profitability [7,8,58]. Interfaces and analytics enable granular pricing, personalized tariffs, and refined segmentation [8,17,57,60]. Blockchain and smart contracts automate transparent, decentralized transactions [5,13,59]. Platform logics such as PAYG, EaaS, and SaaS introduce recurring and modular revenue structures aligned with digitally mediated services [5,18,44,53,61]. Empirically, capture effects are strongest when interfaces (for personalization) and coordination (for automated settlement) are combined with forecasting (for cost discipline), a triad that underpins many observed moves toward dynamic pricing and subscription models. Adaptive pricing and service models allow firms to monetise flexibility and low-carbon services, reinforcing financial and environmental performance.

Propagation across components is not automatic and remains context-dependent. A blockchain deployment limited to provenance can strengthen delivery assurance without shifting monetization, an operational upgrade rather than a new revenue logic. Pay-as-you-go models may be innovative in underserved markets yet merely evolutionary in tightly regulated retail regimes. Digital twins often begin as design-stage tools (creation) and, when linked to live telemetry and user interfaces, evolve into operational decision engines that shape scheduling and pricing (delivery and capture). These cases underscore that a technology's role is application-specific and can sit in different parts of the architecture.

When propagation does occur, effects are mutually reinforcing: improvements in value creation (e.g., visibility and forecasting) spill into delivery (e.g., decentralized scheduling and new channels) and ultimately reshape capture (e.g., granular pricing and novel exchange mechanisms). Conversely, new pricing or exchange mechanisms can pull delivery redesign and alter upstream creation activities. Figure 7 visualizes these interdependencies and feedback across components and motivates the change-type analysis in Section 4.3.

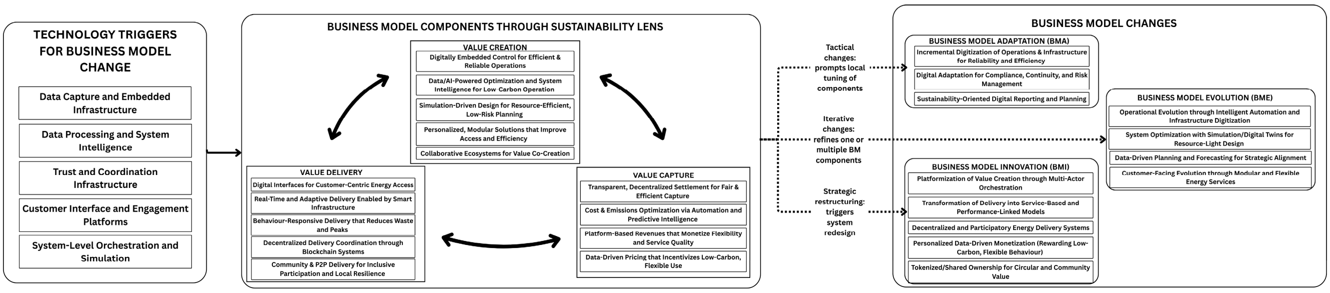

Figure 7. Conceptual Model of Digital-Driven Business Model Change. Arrows indicate how technology triggers act on business model components through a sustainability lens (efficiency, resilience, inclusion) and propagate along the continuum from adaptation (BMA) to evolution (BME) and innovation (BMI).

4.3. Types of Business Model Change Through a Sustainability Lens

This study interprets BM change along three intertwined criteria; degree of change, structural impact (how many and which components are affected), and introduction of new logic, that locate cases on a continuum from adaptation (BMA) through evolution (BME) to innovation (BMI) [25,28,33,35,37,70–72]. The functional mechanisms identified in Section 4.1 and their component-level effects in Section 4.2 provide the pathway through which these change types materialize.

Table 1 summarizes the three BM change types applied in this study. Business model adaptation (BMA) refers to short-term, reactive adjustments to specific components. Business model evolution (BME) describes gradual and coordinated refinement over time. Business model innovation (BMI) represents transformational change in value creation, delivery, and capture. The table consolidates these operationalizations and distinguishes them by degree of change, structural scope, and logic preservation. This distinction guides the analysis in the following subsections.

Table 1. Types of Business Model Change.

Concept	Operationalization in This Study	Key Characteristics
Business Model Adaptation (BMA)	Short-term, reactive adjustments to specific BM components.	Incremental, localized, tactical; no change in core value logic
Business Model Evolution (BME)	Gradual and coordinated refinement of BM components over time.	Internally driven; cumulative learning; improved alignment without altering value logic.
Business Model Innovation (BMI)	Transformational change in how value is created, delivered, and captured.	New value logic; reconfigured delivery and monetization; system-wide impact.

As set out in Section 4.1, we treat digital technologies as functional triggers grouped by the role or mechanism through which they operate, keeping the model simple and extensible so new tools can be placed by function rather than label. Together with Section 4.2, this lens maps how triggers act on value creation, delivery, and capture. Figure 7 presents a single model of these layers: as role-based triggers are layered and aligned across components and partners, they generate outcomes along the BMA–BME–BMI continuum. Read through a sustainability lens, BMA aligns reporting and efficiency; BME enhances system-level efficiency and resilience; BMI enables inclusive, circular and low-carbon value logics. For example, IoT-based monitoring and substation automation in distribution grids (Data Capture and Embedded Infrastructure) improve visibility, predictive maintenance, and reliability in value creation and delivery, illustrating an evolutionary pattern of change (BME) that primarily enhances efficiency and resilience. Likewise, blockchain-enabled peer-to-peer platforms and virtual power plants (Trust and Coordination Infrastructure) introduce new value-capture logics and prosumer participation, exemplifying how coordination architectures can underpin more radical, innovation-oriented changes (BMI) with implications for inclusion and shared value creation. Thus, integration depth links digital roles to sustainability outcomes.

4.3.1. Business Model Adaptation (BMA)

Adaptation captures localized operational or reporting improvements within an unchanged value logic. Illustrative cases include substation automation to enhance reliability in the Portuguese distribution network [63], AI-based scenario planning aligned with SDGs [8], and cognitive digital twins were used for strategic tracking, none of which alter revenue or delivery mechanisms [11]. In the model, BMA corresponds to shallow deployments (typically monitoring/control or design-time simulation) with effects concentrated in a single component, most often value creation or delivery.

4.3.2. Business Model Evolution (BME)

Evolution denotes cross-functional integration and system-level restructuring while the underlying value logic persists. Diagnostics, digital twins, and predictive maintenance improve planning and grid efficiency [7,8,55]. Smart meters and IoT/edge architectures decentralize control and automate delivery decisions without changing actor roles or revenue structures [6,63]. Simulation tools optimize upgrades and design choices without altering pricing or consumption mechanisms [13,58]. In the model, BME arises when monitoring/control, forecasting, and simulation co-operate to affect multiple components (creation and delivery), while interfaces and coordination remain domesticated within existing commercial rules.

4.3.3. Business Model Innovation (BMI)

Innovation involves a structural reconfiguration of how value is created, delivered, and captured through the introduction of new coordination and monetization logics. Blockchain and smart contracts enable peer-to-peer exchange and tokenized ownership that challenge centralized utility structures [23,59]. Mobile-enabled PAYG shifts from asset sales to service access in off-grid settings [61]. EaaS and SaaS subscriptions redefine relationships and pricing [5,44]. AI-enabled personalization supports dynamic bundling and behavioural pricing beyond fixed tariffs [17,57]. In the model, BMI is most likely when interfaces and coordination are combined with forecasting to reassign roles and redesign payments, thereby altering all three components simultaneously.

Trajectories are rarely linear: progress occurs via iterative adjustments that compound across components and partners, layering BMA and BME before BMI emerges [8,23,55]. Business model innovation in the renewable energy sector faces distinctive tensions between technological advancement, regulatory constraints, and sustainability imperatives [73], creating multiple valid pathways for innovation rather than a single optimal model. Crossing from BME to BMI depends less on the presence of any particular tool than on integration depth across components and partners, on interoperability, and on institutional openness (e.g., tariff and settlement regimes) that allow new value logics to operate. For example, mobile-enabled pay-as-you-go (PAYG) systems function as BME in regulated utility contexts where they merely improve payment flexibility within existing delivery channels and utility control, but constitute BMI in off-grid contexts where they introduce prosumer participation, new actor roles, and fundamentally alter how value is captured through service-based micropayment models [61]. Pathways also vary with organizational heritage: incumbents tend to layer upgrades under existing constraints, whereas entrants more readily adopt platform-based designs that enable larger leaps.

Although grounded in renewable energy, the conceptual model is portable to other digitally intensive, infrastructure-dependent sectors (e.g., mobility, logistics, water, and telecom). The generalizability of this framework is supported by cross-sectoral findings on digital transformation and business model change [15], which document similar patterns of technology-enabled business model reconfiguration across the energy, mobility, logistics, and telecommunications sectors. Feasibility and application will differ by sector, but the role-based trigger → component → change-type logic offers a consistent template that can be applied and empirically tested beyond energy. Organisational heritage also matters: smaller entrants can often adopt platform logics faster, whereas incumbents tend to layer changes under legacy constraints. Chapter 5 distils these insights into key contributions and draws out the implications.

5. Conclusions

5.1. Theoretical Contributions

This study offers several contributions to the literature at the intersection of digitalization and business model (BM) change in the renewable energy sector. One of the primary contributions is the introduction of a functional grouping of digital technologies. Rather than analyzing tools like artificial intelligence, blockchain, or digital twins in isolation, this study classifies them according to the roles they perform within business contexts. These include functions such as data monitoring, system optimization, user interaction, decentralized coordination, and strategic simulations. This grouping enables a more abstract and generalizable understanding of digital transformation and helps bridge the gap between technological capabilities and BM outcomes.

Many firms adopt technologies in layers, beginning with real-time monitoring tools such as IoT sensors or smart meters. These foundational tools often enable higher-order technologies like AI, blockchain, or configurator platforms to operate effectively. This layered configuration reflects how digital integration evolves over time and supports increasingly complex value creation and capture mechanisms.

The functional perspective also supports clearer theorization of how digital tools affect different BM components. By focusing on what technologies enable rather than what they are, the study shows how digitalization shapes value creation, delivery, and capture through mechanisms like predictive control, behavioral personalization, and decentralized exchange. This function-based lens helps explain why the same technology may lead to different outcomes across firms and why certain combinations of technologies tend to appear together. The study identified key technologies like AI, IoT, and digital twins, but emphasized that their business relevance depends on functional deployment. The functional groups provide a clearer map of how different tools contribute to strategic change. The study found that digital functions can impact value creation, delivery, and capture in varied and overlapping ways. For example, AI-powered forecasting affects both operations and pricing [4,8,53], while blockchain supports both coordination and monetization [6,11,13,23,44]. These patterns are not fixed but highly context-dependent. The sustainability lens operates across three dimensions: efficiency (reducing technical and economic waste), resilience (enhancing the ability of energy systems and firms to absorb and adapt to shocks), and inclusion (broadening access and participation in energy services). The five digital functional groups contribute to these outcomes in distinct but interconnected ways. Data capture and embedded infrastructure (e.g., IoT sensors, smart meters, substation automation) primarily support efficiency and resilience by improving visibility into generation and consumption, enabling faster fault detection, and informing grid investment decisions; system-dynamics analyses of distribution networks, for instance, show how advanced monitoring and automation can both increase reliability and guide more cost-effective reinforcement strategies [63]. Data processing and system intelligence (e.g., AI- and ML-based forecasting, optimization engines, and digital twins) further enhance efficiency and resilience by reducing forecast errors, optimizing dispatch, and supporting proactive maintenance and planning, thereby improving operational performance and alignment with sustainability-oriented targets in energy enterprises. Customer interface and engagement platforms (e.g., mobile dashboards, cloud portals, and GSM-enabled Pay-As-You-Go systems) enable users to monitor and adapt their consumption in real time while lowering entry barriers for low-income and off-grid households in regions such as Sub-Saharan Africa, directly linking digital engagement to both demand-side efficiency and inclusion [61]; at the same time, these interfaces are implicated in broader debates on "energy democracy," where digital tools shape how citizens participate in and influence energy transitions. Trust and coordination infrastructures (e.g., blockchain platforms, smart contracts, and virtual power plants) foster resilience and inclusion by enabling secure, transparent coordination among distributed prosumers, facilitating local trading and aggregation of distributed resources, and experimenting with new participatory business models such as peer-to-peer trading and community-based VPPs [56,59,64]. Finally, system-level orchestration and simulation tools (e.g., digital twins, scenario-based planning environments, and system-dynamics models) contribute to efficiency and resilience by allowing firms and policymakers to explore alternative configurations of renewable assets, redesign regional "energy valleys," and compare digital versus conventional grid investment pathways under uncertainty before committing to physical deployment [58]. Together, these functional roles illustrate that digitalization can reinforce efficiency, resilience, and inclusion, but the extent to which these sustainability outcomes are realized depends on how technologies are embedded within business models and regulatory and market contexts.

A second theoretical contribution is the integration of this functional view with the typology of BM change. Beyond the functional grouping lens, this work contributes to business model innovation theory by addressing the distinction between wicked problems (ill-defined, context-dependent) and paradigmatic problems (well-defined, generalizable) in business model research [74]. The functional taxonomy approach treats technology roles as paradigmatic while acknowledging that their strategic impact is contextual, offering more nuanced understanding than purely contingency-based approaches. The study interprets changes as adaptation, evolution, or innovation, and connects each to specific digital functions and configurations. Adaptation typically occurred due to internal improvement needs or external pressures, such as policy goals. Evolution involved broader restructuring with continuity in value logic, while innovation represented fundamental shifts in how value is created and delivered.

Finally, by synthesizing fragmented findings from across energy systems, digital innovation, and strategic management literature, the study contributes to a more unified theory of how renewable energy firms use digital tools to reconfigure their BMs. It provides conceptual clarity and analytical structure in a field often marked by disciplinary silos and case-specific insights.

5.2. Practical Contributions

The findings of this study offer several important insights for renewable energy firms managing digital transformation. A key implication is that adopting digital technologies in isolation is unlikely to deliver strategic impact. Instead, firms should focus on aligning technologies with specific BM priorities. For instance, firms aiming for personalized offerings should integrate analytics-enabled platforms, while those focused on grid efficiency may prioritize forecasting engines and simulation tools. The study also highlights the importance of sequencing. Digital transformation often unfolds in layers and our findings suggest a four-step logic grounded in the functional groupings: first, firms consolidate foundational visibility and control through data capture and embedded infrastructure (IoT sensors, smart meters, monitoring, automation); second, they build system intelligence and simulation capabilities (AI/ML forecasting, optimization, digital twins); third, they extend digitalization to customer-side and ecosystem interfaces (mobile apps, portals, configurators, PAYG systems); and fourth, they experiment with decentralized coordination and new market logics (blockchain, P2P trading, VPPs, platforms). Firms that progress broadly along this sequence can better align digital investments with coherent trajectories of business model adaptation, evolution, or innovation, while advancing efficiency, resilience, and inclusion outcomes. Firms should therefore approach digitalization as a cumulative process, building robust digital infrastructure before deploying advanced applications.

The functional grouping developed in this study offers a practical framework for assessing digital capabilities. By understanding technologies through their roles such as monitoring, coordination, or user interaction, firms can identify gaps, evaluate synergies, and prioritize technologies that best support their strategic goals. This function-based view also helps firms avoid tool-centric approaches and instead build coherent digital strategies rooted in business outcomes. Practically, the functional-mechanism lens also helps managers sequence digital investments that advance both BM change and sustainability outcomes (efficiency, resilience, and inclusion), offering a replicable pathway for asset-intensive sectors.

Firms should expect to combine adaptive improvements with more structural evolutions and occasional innovations over time. Recognizing digital transformation as an ongoing, layered process can help firms better manage risks, maintain coherence, and sustain long-term competitiveness.

Finally, enabling this transformation will require supportive regulatory frameworks [3–5,10,23]. Policymakers should ensure legal clarity around smart contracts, promote interoperability standards, and create conditions for emerging BMs such as peer-to-peer trading and service-based energy delivery. Regulation that keeps pace with digital innovation will be essential for scaling firm-level experimentation into broader system change.

Despite their promise, digital integrations face recurring constraints. Data and security issues (sensor fidelity, incomplete datasets, and cybersecurity/privacy tensions) reduce AI reliability and complicate ledger immutability [4,17,23]. Technical barriers include legacy interoperability and the computational demands of AI/IoT/blockchain stacks [8,54]. Economic hurdles, up-front infrastructure costs and uncertain ROI in capped-tariff contexts, deter smaller firms [18]. Organizational gaps in skills and governance slow cross-actor coordination [3,12]. Regulatory ambiguity around smart contracts/peer-to-peer models and weak interoperability enforcement persist [10,23]. Ethical concerns (digital exclusion, automation-led job loss, data misuse, and environmental footprints) require deliberate mitigation [7,55]. These boundary conditions shape feasible integration depth and help explain the variation in the observed change types.

5.3. Research Limitations

While this study offers a structured synthesis of how digital technologies influence BM change in renewable energy firms, it has several limitations that open opportunities for further research. A fundamental methodological constraint is that, as a systematic literature review, the study draws exclusively from published academic sources and does not incorporate empirical data from within firms. Although the Gioia methodology enabled rigorous and transparent coding, findings rest on secondary interpretations rather than primary data. This constraint is compounded by the review's reliance on Scopus and English-language peer-reviewed articles, which introduces selection bias toward established, Anglophone scholarship. This likely underrepresents work in non-English-speaking regions (such as China) with significant renewable energy sectors and distinct regulatory contexts. Together, these limitations mean the study captures what is published in English-language journals but misses emerging practices, regional variations, and practitioner insights from non-Anglophone markets. Future research could address these constraints by combining case studies, interviews, and longitudinal methods with non-English sources, industry reports, and ethnographic fieldwork to validate the patterns identified here and illuminate contextual dimensions absent from academic literature.

Another limitation is that while the study examines the functional roles of digital technologies, it does not assess the depth of their integration into firm operations and BM architecture. The same digital tool may lead to very different outcomes depending on how deeply it is embedded in a firm's processes, infrastructure, and strategic systems. A shallow implementation might result in minor efficiency gains, while deep integration could enable more fundamental transformation. This difference likely influences not only the scale of change but also whether firms experience adaptation, evolution, or innovation in their BMs. This assessment is complicated by real-world implementation barriers. Data quality issues, cybersecurity vulnerabilities, and interoperability constraints identified throughout the literature directly affect whether assumed causal pathways materialize as theorized. Additionally, emerging technologies (5G, quantum computing, etc.) may fundamentally reshape which functional roles are viable or dominant post-2025, requiring the model to be revisited as the technology landscape evolves. Furthermore, the review does not systematically examine why identical digital technologies produce different BM outcomes across firms. While findings reveal heterogeneous transformation pathways, the moderating factors explaining these differences such as firm size, digital maturity, organizational heritage, and institutional context remain underexplored in the reviewed literature, limiting the model's explanatory power for predicting outcomes across diverse firm contexts.

A key limitation is also that this review does not systematically examine how regulatory and policy frameworks shape digital adoption and BM change types. Tariff regulation, data governance requirements, interoperability standards, and smart contract legal clarity significantly influence whether firms pursue incremental adaptation versus radical innovation. Future research should investigate the moderating effects of regulatory environments on digital-driven BM transformation.

These limitations directly inform the future research agenda in Section 5.4. Specifically, the reliance on secondary data and lack of longitudinal evidence motivates studies of sequential BM change pathways (RQ1–RQ4). The English-language and Scopus-centric scope calls for research in non-Anglophone contexts such as China (RQ6). And the emergent nature of moderating factors (firm size, digital maturity, regulatory regimes) suggests empirical work to test their boundary conditions (RQ5).

5.4. An Agenda for Future Research

Building on this observation, future research should explore the concept of digital integration depth as a key determinant of BM change. This would involve studying not just what technologies are adopted but how extensively and coherently they are embedded across value creation, delivery, and capture mechanisms. A particularly promising direction concerns the heterogeneity of transformation pathways across firm types. Evidence suggests start-ups and incumbents follow distinct business model change trajectories when adopting digital technologies [75,76]. Startups typically adopt platform-based, innovative business models more readily, while incumbents tend to layer digital improvements within existing constraints. Future research should investigate whether this difference reflects organizational capabilities, regulatory constraints, or strategic choice. Understanding these patterns at the firm level can provide a more detailed view of how digital transformation unfolds over time. While deeper integration can enable more fundamental transformation, digitalization does not guarantee sustainability; rebound effects and governance gaps may offset gains. This underscores the need for outcome measurement alongside mapping integration depth.

To guide such inquiry, we propose the following research question:

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

Beyond this core question, several additional thematic gaps emerged from the literature analysis that point to promising directions for future research. Table 2 below outlines underexplored areas and corresponding research questions organized by theme.

Table 2. Future Research Directions Across Key Themes in Digital-Enabled Business Model Change.

Main Theme	Gaps/Underexplored Areas	Potential Research Questions
Business Model Dynamics in RE Sector	1. Lack of longitudinal studies mapping sequential BM changes. 2. Limited understanding of transitions between BMA, BME, and BMI in real firms.	RQ1: How do renewable energy firms move between adaptation, evolution, and innovation in response to digital integration? RQ2: What patterns of business model dynamics can be observed 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 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 like capabilities, leadership, and regulation.	RQ5: How do firm size, digital capabilities, and external conditions, moderate the impact of digital technologies on business model change in the renewable energy sector?
Moderating Factors and Regulatory Context	1. Heterogeneity in outcomes across firm types not systematically explored. 2. Regulatory and policy frameworks' moderating role on digital-driven BM change	RQ6: Why do identical digital technologies produce different business model outcomes across firms, and how do moderating factors such as firm size, digital maturity, organizational heritage, and institutional context shape transformation pathways? RQ7: To what extent do regulatory frameworks (tariff structures, data governance requirements, interoperability standards, and smart contract legality) constrain or enable different types of business model change (adaptation, evolution, or innovation) in renewable energy firms adopting digital technologies?

These directions extend the conceptual foundation developed in this study and open avenues for comparative, longitudinal, and firm-level research. Exploring these questions empirically can help build a more nuanced understanding of digital transformation processes and offer valuable insights for both academic theorization and strategic decision-making in renewable energy and related sectors.

https://doi.org/10.3390/systems14030269

5.5. Final Reflection

This study set out to understand how digital technologies shape BM change in the renewable energy sector. By synthesizing insights from across disciplines and organizing them through a functional lens, this study provides a clearer picture of how digital tools enable firms to reconfigure value creation, delivery, and capture. The findings show that digital transformation is not a uniform or one-directional process. Instead, it unfolds in layered, context-specific ways, with firms combining foundational tools and advanced applications to meet strategic goals.

Rather than focusing on individual technologies, this study emphasizes what these technologies do. This function-based perspective offers a more flexible and transferable framework for analysing BM change. It helps explain how the same tool can lead to different outcomes and why similar outcomes may be achieved using different configurations. By linking functional roles to types of change, this study contributes to a more nuanced understanding of digital BM transformation in the renewable energy sector.

Ultimately, the path forward for both research and practice lies in recognizing that digitalization is not just a technical upgrade but a strategic re-composition of how firms create, deliver, and capture value. As renewable energy firms continue to adapt to regulatory shifts, customer expectations, and technological advances, their ability to align digital capabilities with evolving BMs will be a key factor in their long-term competitiveness and impact.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/systems14030269/s1. Table S1: PRISMA checklist for the systematic literature review "Digital Technologies as Drivers of Business Model Change in Renewable Energy Firms".

Author Contributions: Conceptualization, P.T. and H.K.; methodology, P.T. and H.K.; formal analysis, P.T.; investigation, P.T.; data curation, P.T.; writing—original draft preparation, P.T.; writing—review and editing, P.T., H.K., J.R.O. and G.K.; visualization, P.T. and H.K.; supervision, H.K. and J.R.O.; project administration, H.K. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: No new data were created or analyzed in this study. Data supporting the findings are derived from the Scopus database and the published articles cited in this review; no additional datasets were generated or analyzed.

Conflicts of Interest: The authors declare no conflict of interest.

Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial Intelligence
IoT	Internet of Things
BM	Business Model
BMA	Business Model Adaptation
BME	Business Model Evolution
BMI	Business Model Innovation
SLR	Systematic Literature Review
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
ML	Machine Learning
PAYG	Pay-As-You-Go
P2P	Peer-to-Peer
VPP	Virtual Power Plant
EaaS	Energy-as-a-Service
EMS	Energy Management System

References

1. Bähr, K.; Fliaster, A. The twofold transition: Framing digital innovations and incumbents' value propositions for sustainability. *Bus. Strategy Environ.* **2023**, *32*, 920–935. [CrossRef]
2. Ciulli, F.; Kolk, A.; Bidmon, C.M.; Sprong, N.; Hekkert, M.P. Sustainable business model innovation and scaling through collaboration. *Environ. Innov. Soc. Transit.* **2022**, *45*, 289–301. [CrossRef]
3. Malewska, K.; Cyfert, S.; Chwiłkowska-Kubala, A.; Mierzejewska, K.; Szumowski, W. The missing link between digital transformation and business model innovation in energy SMEs: The role of digital organisational culture. *Energy Policy* **2024**, *192*, 114254. [CrossRef]
4. Ahmad, T.; Zhang, D.; Huang, C.; Zhang, H.; Dai, N.; Song, Y.; Chen, H. Artificial intelligence in sustainable energy industry: Status Quo, challenges and opportunities. *J. Clean. Prod.* **2021**, *289*, 125834. [CrossRef]
5. Gitelman, L.; Kozhevnikov, M. New business models in the energy sector in the context of revolutionary transformations. *Sustainability* **2023**, *15*, 3604. [CrossRef]
6. Augello, A.; Gallo, P.; Sanseverino, E.R.; Sciumè, G.; Tornatore, M. A Coexistence Analysis of Blockchain, SCADA Systems, and OpenADR for Energy Services Provision. *IEEE Access* **2022**, *10*, 99088–99101. [CrossRef]
7. D'Amore, G.; Di Vaio, A.; Balsalobre-Lorente, D.; Boccia, F. Artificial Intelligence in the Water–Energy–Food Model: A Holistic Approach towards Sustainable Development Goals. *Sustainability* **2022**, *14*, 867. [CrossRef]
8. Franki, V.; Majnarić, D.; Višković, A. A Comprehensive Review of Artificial Intelligence (AI) Companies in the Power Sector. *Energies* **2023**, *16*, 1077. [CrossRef]
9. Zhao, Y.; Xia, S.; Zhang, J.; Hu, Y.; Wu, M. Effect of the Digital Transformation of Power System on Renewable Energy Utilization in China. *IEEE Access* **2021**, *9*, 96201–96209. [CrossRef]
10. Hu, B.; Zhou, P.; Zhang, L.P. A digital business model for accelerating distributed renewable energy expansion in rural China. *Appl. Energy* **2022**, *316*, 119084. [CrossRef]
11. Ciano, M.P.; Peron, M.; Panza, L.; Pozzi, R. Industry 4.0 technologies in support of circular Economy: A 10R-based integration framework. *Comput. Ind. Eng.* **2025**, *201*, 110867. [CrossRef]
12. Del Vecchio, P.; Massaro, A.; Garzoni, A. Circular value creation and business process management for twin transition: The case of an energy company. *Comput. Ind. Eng.* **2025**, *201*, 110936. [CrossRef]
13. Singh, M.; Jiao, J.; Klobasa, M.; Frietsch, R. Making Energy-transition headway: A Data driven assessment of German energy startups. *Sustain. Energy Technol. Assess.* **2021**, *47*, 101322. [CrossRef]
14. Cavalcante, S.; Kesting, P.; Ulhøi, J.P. Business model dynamics and innovation: (Re)establishing the missing linkages. *Manag. Decis.* **2011**, *49*, 1327–1342. [CrossRef]
15. Trischler, M.F.G.; Li-Ying, J. Digital business model innovation: Toward construct clarity and future research directions. *Rev. Manag. Sci.* **2023**, *17*, 3–32. [CrossRef]
16. Spieth, P.; Schneckenberg, D.; Ricart, J.E. Business model innovation—State of the art and future challenges for the field. *R D Manag.* **2014**, *44*, 237–247. [CrossRef]
17. Bartczak, K. Digital Technology Platforms as an Innovative Tool for the Implementation of Renewable Energy Sources. *Energies* **2021**, *14*, 7877. [CrossRef]
18. Pakulska, T.; Poniatowska-Jaksch, M. Digitalization in the Renewable Energy Sector—New Market Players. *Energies* **2022**, *15*, 4714. [CrossRef]
19. Minatogawa, V.; Franco, M.; Rampasso, I.S.; Holgado, M.; Garrido, D.; Pinto, H.; Quadros, R. Towards systematic sustainable business model innovation: What can we learn from business model innovation. *Sustainability* **2022**, *14*, 2939. [CrossRef]
20. Dhir, A.; Khan, S.J.; Islam, N.; Ractham, P.; Meenakshi, N. Drivers of sustainable business model innovations. An upper echelon theory perspective. *Technol. Forecast. Soc. Change* **2023**, *191*, 122409. [CrossRef]
21. Boons, F.; Lüdeke-Freund, F. Business models for sustainable innovation: State-of-the-art and steps towards a research agenda. *J. Clean. Prod.* **2013**, *45*, 9–19. [CrossRef]
22. Saunila, M.; Nasiri, M.; Ukko, J.; Rantala, T. Smart technologies and corporate sustainability: The mediation effect of corporate sustainability strategy. *Comput. Ind.* **2019**, *108*, 178–185. [CrossRef]
23. Mika, B.; Goudz, A. Blockchain-technology in the energy industry: Blockchain as a driver of the energy revolution? *Energy Rep.* **2021**, *7*, 4511–4524. [CrossRef]
24. Bartczak, K.; Łobejko, S. The Implementation Environment for a Digital Technology Platform of Renewable Energy Sources. *Energies* **2022**, *15*, 5793. [CrossRef]
25. Teece, D.J. Business models, business strategy and innovation. *Long Range Plan.* **2010**, *43*, 172–194. [CrossRef]
26. Atkova, I.; Galkina, T.; Yang, M.; Leposky, T.; Ahokangas, P. Opening the black box of transition towards a sustainable business model. *Long Range Plan.* **2025**, *58*, 102499. [CrossRef]
27. Richardson, J. The business model: An integrative framework for strategy execution. *Strateg. Change* **2008**, *17*, 133–144. [CrossRef]

28. Zott, C.; Amit, R.; Massa, L. The business model: Recent developments and future research. *J. Manag.* **2011**, *37*, 1019–1042. [CrossRef]
29. Lepak, D.P.; Smith, K.G.; Taylor, M.S. Value creation and value capture: A multilevel perspective. *Acad. Manag. Rev.* **2007**, *32*, 180–194. [CrossRef]
30. Carayannis, E.G.; Sindakis, S.; Walter, C. Business Model Innovation as Lever of Organizational Sustainability. *J. Technol. Transf.* **2015**, *40*, 85–104. [CrossRef]
31. Campana, P.; Censi, R.; Ruggieri, R.; Amendola, C. Smart Grids and Sustainability: The Impact of Digital Technologies on the Energy Transition. *Energies* **2025**, *18*, 2149. [CrossRef]
32. Desyllas, P.; Sako, M. Profiting from business model innovation: Evidence from Pay-As-You-Drive auto insurance. *Res. Policy* **2013**, *42*, 101–116. [CrossRef]
33. Massa, L.; Tucci, C.L. Business model innovation. *Oxf. Handb. Innov. Manag.* **2013**, *20*, 420–441.
34. Zott, C.; Amit, R. The business model: A theoretically anchored robust construct for strategic analysis. *Strateg. Organ.* **2013**, *11*, 403–411. [CrossRef]
35. Foss, N.J.; Saebi, T. Fifteen years of business model innovation research: Past accomplishments, future challenges. *J. Manag.* **2017**, *43*, 200–227. [CrossRef]
36. Massa, L.; Tucci, C.L.; Afuah, A. A critical assessment of business model research. *Acad. Manag. Ann.* **2017**, *11*, 73–104. [CrossRef]
37. Demil, B.; Lecocq, X. Business model evolution: In search of dynamic consistency. *Long Range Plan.* **2010**, *43*, 227–246. [CrossRef]
38. Saebi, T. Business model evolution, adaptation or innovation? A contingency framework. In *Business Model Innovation: The Organizational Dimension*; Oxford University Press: Oxford, UK, 2014. [CrossRef]
39. Peñarroya-Farell, M.; Miralles, F. Business model dynamics from interaction with open innovation. *J. Open Innov. Technol. Mark. Complex.* **2021**, *7*, 81. [CrossRef]
40. Amit, R.; Zott, C. Creating value through business model innovation. *MIT Sloan Management Review*, 20 March 2012.
41. Wang, Z.; Lin, S.; Chen, Y.; Lyulyov, O.; Pimonenko, T. Digitalization Effect on Business Performance: Role of Business Model Innovation. *Sustainability* **2023**, *15*, 9020. [CrossRef]
42. Gioia, D.A.; Corley, K.G.; Hamilton, A.L. Seeking qualitative rigor in inductive research: Notes on the Gioia methodology. *Organ. Res. Methods* **2013**, *16*, 15–31. [CrossRef]
43. Tranfield, D.; Denyer, D.; Smart, P. Towards a methodology for developing evidence-informed management knowledge by means of systematic review. *Br. J. Manag.* **2003**, *14*, 207–222. [CrossRef]
44. Sułek, A.; Borowski, P.F. Business Models on the Energy Market in the Era of a Low-Emission Economy. *Energies* **2024**, *17*, 3235. [CrossRef]
45. Endres, S.; Weibler, J. Towards a three-component model of relational social constructionist leadership: A systematic review and critical interpretive synthesis. *Int. J. Manag. Rev.* **2017**, *19*, 214–236. [CrossRef]
46. Dada, O.L. A model of entrepreneurial autonomy in franchised outlets: A systematic review of the empirical evidence. *Int. J. Manag. Rev.* **2018**, *20*, 206–226. [CrossRef]
47. Page, M.J.; McKenzie, J.E.; Bossuyt, P.M.; Boutron, I.; Hoffmann, T.C.; Mulrow, C.D.; Shamseer, L.; Tetzlaff, J.M.; Akl, E.A.; Brennan, S.E.; et al. The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *BMJ* **2021**, *372*, n71. [CrossRef]
48. Gehman, J.; Glaser, V.L.; Eisenhardt, K.M.; Gioia, D.A.; Langley, A.; Corley, K.G. Finding theory–method fit: A comparison of three qualitative approaches to theory building. *J. Manag. Inq.* **2018**, *27*, 284–300. [CrossRef]
49. Timmermans, S.; Tavory, I. Theory construction in qualitative research: From grounded theory to abductive analysis. *Sociol. Theory* **2012**, *30*, 167–186. [CrossRef]
50. Kolagar, M.; Parida, V.; Sjödin, D. Ecosystem transformation for digital servitization: A systematic review, integrative framework, and future research agenda. *J. Bus. Res.* **2022**, *146*, 176–200. [CrossRef]
51. Shenton, A. Strategies for Ensuring Trustworthiness in Qualitative Research Projects. *Educ. Inf.* **2004**, *22*, 63–75. [CrossRef]
52. Birt, L.; Scott, S.; Cavers, D.; Campbell, C.; Walter, F. Member Checking: A Tool to Enhance Trustworthiness or Merely a Nod to Validation? *Qual. Health Res.* **2016**, *26*, 1802–1811. [CrossRef] [PubMed]
53. Anantha Subramanya Iyer, K.N.; Mahalakshmi, S.; Desai, K.; Hemanth Kumar, S.; Kautish, S. Optimizing Green Power and Green Energy Through Digital Technologies. In *Digital Technologies to Implement the UN Sustainable Development Goals*; Leal Filho, W., Kautish, S., Wall, T., Rewhorn, S., Paul, S.K., Eds.; Springer Nature: Cham, Switzerland, 2024; pp. 275–304. [CrossRef]
54. Liu, J.; Huang, Z.; Fan, M.; Yang, J.; Xiao, J.; Wang, Y. Future energy infrastructure, energy platform and energy storage. *Nano Energy* **2022**, *104*, 107915. [CrossRef]
55. Muhammad Adnan Zahid, H.; Zulfiqar, A.; Sajid Iqbal, M.; Shah, A.; Fida, K. Global Renewable Energy Transition: A Multidisciplinary Analysis of Emerging Computing Technologies, Socio-Economic Impacts, and Policy Imperatives. *Eng. Arch.* **2024**. [CrossRef]

56. Plewnia, F. The Energy System and the Sharing Economy: Interfaces and Overlaps and What to Learn from Them. *Energies* **2019**, *12*, 339. [CrossRef]
57. Vom Scheidt, F.; Staudt, P. A data-driven Recommendation Tool for Sustainable Utility Service Bundles. *Appl. Energy* **2024**, *353*, 122137. [CrossRef]
58. Skaloumpakas, P.; Sarmas, E.; Rachmanidis, M.; Marinakis, V. Reshaping the energy landscape of Crete through renewable energy valleys. *Sci. Rep.* **2024**, *14*, 8038. [CrossRef]
59. Neska, E.; Kowalska-Pyzalska, A. Conceptual design of energy market topologies for communities and their practical applications in EU: A comparison of three case studies. *Renew. Sustain. Energy Rev.* **2022**, *169*, 112921. [CrossRef]
60. Yu, Y.; Ren, F.; Ju, Y.; Zhang, J.; Liu, X. Exploring the Role of Digital Transformation and Breakthrough Innovation in Enhanced Performance of Energy Enterprises: Fresh Evidence for Achieving Sustainable Development Goals. *Sustainability* **2024**, *16*, 650. [CrossRef]
61. Rasagam, G.; Zhu, D. Delivering on the Promise of Distributed Renewable Energy Entrepreneurship in Sub-Saharan Africa. *Curr. Sustain. Renew. Energy Rep.* **2018**, *5*, 230–239. [CrossRef]
62. Nosova, O.; Grytsenko, A.; Lypov, V. Cooperative digital platforms in the renewable energy sector. *Intellect. Econ.* **2023**, *18*, 214–230. [CrossRef]
63. Leiva Vilaplana, J.A.; Yang, G.; Monaco, R.; Bergaentzlé, C.; Ackom, E.; Morais, H. Digital versus grid investments in electricity distribution grids: Informed decision-making through system dynamics. *Appl. Energy* **2025**, *386*, 125536. [CrossRef]
64. Venkatachary, S.K.; Prasad, J.; Samikannu, R. Challenges, Opportunities and Profitability in Virtual Power Plant Business Models in Sub Saharan Africa—Botswana. *Int. J. Energy Econ. Policy* **2017**, *7*, 48–58.
65. Sosna, M.; Trevinyo-Rodríguez, R.N.; Velamuri, S.R. Business model innovation through trial-and-error learning. *Long Range Plan.* **2010**, *43*, 383–407. [CrossRef]
66. Wirtz, B.W.; Pistoia, A.; Ullrich, S.; Göttel, V. Business models: Origin, development and future research perspectives. *Long Range Plan.* **2016**, *49*, 36–54. [CrossRef]
67. Teece, D.J. Business models and dynamic capabilities. *Long Range Plan.* **2018**, *51*, 40–49. [CrossRef]
68. McGrath, R.G. Business models: A discovery driven approach. *Long Range Plan.* **2010**, *43*, 247–261. [CrossRef]
69. Geissdoerfer, M.; Vladimirova, D.; Evans, S. Sustainable business model innovation: A review. *J. Clean. Prod.* **2018**, *198*, 401–416. [CrossRef]
70. Balboni, B.; Bortoluzzi, G. Business model adaptation and the success of new ventures. *J. Entrep. Manag. Innov.* **2015**, *11*, 119–140. [CrossRef]
71. Chesbrough, H. Business model innovation: Opportunities and barriers. *Long Range Plan.* **2010**, *43*, 354–363. [CrossRef]
72. Khodaei, H.; Ortt, R. Capturing dynamics in business model frameworks. *J. Open Innov. Technol. Mark. Complex.* **2019**, *5*, 8. [CrossRef]
73. Laur, I.; Berntzen, L. Opposing forces of business model innovation in the renewable energy sector: Alternative patterns and strategies. *Int. J. Entrep. Innov.* **2023**. [CrossRef]
74. Foss, N.J.; Saebi, T. Business models and business model innovation: Between wicked and paradigmatic problems. *Long Range Plan.* **2018**, *51*, 9–21. [CrossRef]
75. Guckenbiehl, P.; Corral De Zubielqui, G. Start-ups' business model changes during the COVID-19 pandemic: Counteracting adversities and pursuing opportunities. *Int. Small Bus. J. Res. Entrep.* **2022**, *40*, 150–177. [CrossRef] [PubMed]
76. Philippi, S.; Heinz, A.; Kabous, L. How Swiss start-ups deal with business model innovation. *Eur. Conf. Innov. Entrep.* **2022**, *17*, 408–415. [CrossRef]