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From connectivity to data ecosystems: a progression framework for IoT business models

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Abstract
The rapid advancement of IoT technologies has enabled new forms of data flow among devices, people, and organizations. This has brought about the emergence of innovative business models with increasingly sophisticated value propositions. This study develops a typology and progression framework for IoT business models, highlighting how value creation and capture evolve as firms integrate IoT technologies. Based on a systematic literature review and multiple case studies, the present research identifies three distinct business model archetypes—namely, connectivity, servitization, and data ecosystems. Each archetype is characterized by specific mechanisms of value creation and capture. The resulting framework provides insights into support firms seeking to align IoT investments with their capabilities and market positioning. By offering a structured view of business model sophistication, this study contributes to the theoretical understanding of IoT business models, business model sophistication, and data ecosystems, while also informing managerial practice.

Keywords IoT business model · Progression framework · Data ecosystem · Servitization · Connectivity · Typology

JEL Classification L86 · O33 · D23

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1 Introduction

The Internet of Things (IoT) has long been viewed as a cornerstone of future digital applications in various industries (Nicolescu et al. 2018). Recognized as one of the most disruptive technologies of the industry 4.0 revolution, IoT integrates physical objects into a large network, fundamentally transforming how individuals and systems interact (Oberländer et al. 2018a, b). Developed around interconnected devices with "the mandatory capabilities of communication and optional capabilities of sensing, actuation, data capture, data storage and data processing" (ITU-T 2012), IoT is conceptualized as a complex system of systems that drives further advancements in the digital economy. Scholars and industry leaders alike suggest that IoT is on track to become the quintessential ubiquitous technology (McKinsey 2015; Gartner 2017). With the potential to revolutionize applications across diverse domains, including education, healthcare, agriculture, and the aeronautics industry, IoT is expected to have a profound impact on nearly all aspects of life (Nicolescu et al. 2018).

The diversity of the applications and innovative use cases of IoT has made it a significant economic force with vast business potential. It is estimated that, by 2030, IoT could generate up to $12.6 trillion in economic value worldwide, encompassing the value captured by both consumers and business customers of IoT products and services (Chui et al. 2023). IoT also enables servitization (Boehmer et al. 2020), defined as the strategic transformation through which firms move from offering standalone products to providing integrated product–service systems. In this way, value is increasingly created and captured through services rather than solely through physical goods, as companies shift toward becoming service providers (Baines et al. 2009; Boehmer et al. 2020).

However, the realization of this immense potential is contingent on firms' ability to adopt and implement viable business models to address the unique characteristics of IoT technology. Business models serve as the critical interface between technological innovation and economic value creation and enable firms to translate IoT capabilities, such as real-time data collection, predictive analytics, and automation, into valuable offerings. Therefore, without a well-structured business model, firms may struggle to effectively monetize IoT-generated data or integrate IoT-driven insights into their value propositions. Thus, the design and evolution of IoT-specific business models are not merely operational considerations but strategic imperatives for firms aiming to capture their share of IoT-enabled economic value.

The existing literature on business model innovation provides a variety of frameworks (Ramdani et al. 2019; Wirtz and Daiser 2017) and models (Chesbrough and Rosenbloom 2002; Jin et al. 2021; Johnson et al. 2008; Lorenz et al. 2024; Mostaghel et al. 2022; Oghazi et al. 2026; Osterwalder et al. 2011; Palmié et al. 2025) to describe and explain how firms can structure their business model and create and capture value. And more specifically, IoT business model literature (e.g., Almeida et al. 2020; Das 2022; Endres et al. 2019; Toorajipour 2025; Wirtz et al. 2019) offers important insights, yet many IoT innovations face significant challenges in identifying viable business models (Endres et al. 2019). Moreover, significant gaps remain in fully understanding critical aspects of IoT business models, including how they evolve over time, the mechanisms by which they create and capture value, and their broader implications. Addressing these overlooked dimensions is essential to unlock the full potential of IoT business models and to provide firms with actionable strategies for navigating this complex and dynamic landscape. This research is driven by the identification of two main challenges: a misconception surrounding the use of IoT business models and a blind spot in the utilization of IoT data.

The misconception surrounding IoT is linked to the use of IoT business models and value creation based on the IoT-generated data. The majority of the literature on IoT business models tends to adopt a one-size-fits-all perspective, presenting these models as stable and universally applicable across organizations (e.g., Ahmad and Zhang 2021; Cranmer et al. 2022; Das 2022; Haaker et al. 2021; Palmié et al. 2022). This approach overlooks the significant variability in how companies utilize IoT technologies and business models. Firms operate in diverse business contexts, possess varying levels of IoT infrastructure, and deploy IoT at different scales. Similarly, the data generated by IoT systems vary in volume, type, complexity, and purpose, reflecting the distinct objectives for which the focal companies employ IoT. Furthermore, the application of IoT may be confined to a single organization or extend to an interconnected network involving multiple actors, each contributing to and deriving value from this network. Such differences profoundly shape the nature and structure of IoT business models and underscore the need for research that incorporates these variations. Thus, a more nuanced understanding of IoT business models is essential for capturing the diverse ways firms leverage IoT.

The second challenge is linked to the unused data generated by IoT and the unrealized potential value that could be captured through its effective utilization. Despite a growing number of success stories, many companies have yet to capture significant benefits from IoT (Gimpel 2020). One of the principal reasons is that IoT data is underutilized or not used at all. Various reports have highlighted that organizations commonly face challenges in effectively utilizing their IoT data (IoT Advisory Board 2024; McKinsey 2015; McKinsey 2018). Research has shown that this is not necessarily a technology issue but rather a business model problem (Ehret and Wirtz 2017; Endres et al. 2019). The mismatch between the vast amounts of data generated by IoT and firms' business models is a critical issue that can prevent the effective harnessing of this unused capacity. IoT-connected sensors, devices, machines, and products produce an unprecedented volume of data, yet much of this potential remains untapped due to the absence of appropriate business models to capture and transform these data into actionable insights.

Beyond identifying viable IoT business models, there is a critical need to understand the archetypes and how these models progress in sophistication. This approach not only enables firms to implement a business model aligned with their data but also provides insights into models they can adopt to better capitalize on their data resources. In this sense, business model sophistication refers to a firm's ability to capture value beyond its core offering by leveraging secondary revenue streams or cost-saving opportunities, often involving higher complexity through complementary offerings and multi-actor value creation (Battistella et al. 2021; Kesting and Günzel-Jensen 2015). This lack of a progression framework presents a significant challenge, as firms require structured guidance on the dynamics of IoT business model development and their strategic and operational implications. Addressing this gap is essential to enable organizations to fully capitalize on the opportunities presented by IoT technologies. This research addresses the following research questions:

A. What are the business model archetypes based on IoT data utilization?
B. How do these models progress in terms of business model sophistication?

By addressing these questions, this study contributes to the literature on IoT business models while also offering practitioners a framework to develop more effective business model components. This framework not only facilitates the alignment of IoT-related initiatives but also helps companies enhance customer value and optimize their IoT-linked value-capture mechanisms. Building on the work of Toorajipour (2025), the present study adopts an exploratory approach to examine IoT-enabled business models.

2 Theoretical background

2.1 The business model concept

The concept of the business model has been a central theme in management literature for many years. Since the late 1990s, the term has gained widespread popularity, particularly within the managerial literature (Demil and Lecocq 2010). Every enterprise adopts a business model either explicitly or implicitly (Filser et al. 2021). Business models are frequently employed to define the fundamental components of a business, with increasing relevance in e-business and research on digital enterprises (Hedman and Kalling 2003). Despite its extensive use across various streams of the business and management literature, the term has often been misinterpreted (DaSilva and Trkman 2014), primarily due to its overlap with related concepts such as “strategy” and “tactics” (Matricano 2020). Additionally, in the information systems (IS) literature, the business model concept has been criticized for its ambiguity, superficiality, and lack of theoretical foundation (Hedman and Kalling 2003). However, when approached with a theoretically rigorous definition, business model research can provide significant contributions, particularly in IS research, as it integrates strategic perspectives such as the resource-based view and industrial organization theories (Hedman and Kalling 2003).

In this study, a business model is conceptualized as a constellation of related activities in which key elements of value creation, value delivery, and value capture are interlinked (Zott and Amit 2010). While various definitions exist, there is broad consensus that a business model is the mechanism by which a firm creates, delivers, and captures value (Amit and Zott 2001; Teece 2010). Thus, a business model represents a firm’s business logic and how it operates to generate value. Fundamentally, the business model concept emphasizes value creation and capture by shifting the analytical focus from the firm itself (Costa Climent and Haftor 2021) to system activities executed through resource coordination and transactions (Amit and Zott 2001; Zott and Amit 2010).

The primary components of a business model include value creation and capture. Value creation refers to the process by which a firm develops products or services that deliver benefits to customers, enhance satisfaction, and fulfill their needs (Amit and Zott 2001). This component is central to a company's ability to attract and retain customers, build strong relationships, differentiate itself from competitors, and sustain long-term growth (Amit and Zott 2001). Value capture, in contrast, determines how offerings are monetized and translated into revenue streams, ultimately ensuring profitability and firm survival (Chesbrough 2007). The effective alignment of value creation and value capture is critical, as it enables firms to deliver value to customers while retaining a share of that value to ensure long-term financial viability (Amit and Zott 2001; Zott and Amit 2010). In the same vein, as value creation and capture increasingly depend on how firms structure relationships among multiple actors, business models become tightly interlinked with business ecosystems (Jacobides et al. 2018). Business model design, therefore, extends beyond the focal firm to include the definition of ecosystem roles, rules, connections, and monetization mechanisms that jointly enable value creation and appropriation (Jacobides et al. 2018).

2.2 IoT business models

Digital transformation has had a major impact on businesses and wide-ranging implications for firms (Kallmuenzer et al. 2025). Specifically, the diffusion of digital technologies, such as IoT, has triggered the extant business model of various companies (D'Angelo et al. 2024). Therefore, technologies such as IoT have attracted considerable attention from academics and professionals (Chopra et al. 2024). IoT represents a global infrastructure for information, facilitating advanced services by interconnecting physical and virtual objects through existing and evolving interoperable information and communication technologies (Kiran 2019). It comprises a network of interconnected devices—including mechanical and digital machines, objects, animals, and humans—each equipped with unique identifiers that enable data transfer over a network without requiring human-to-human or human-to-computer interaction (Kiran 2019). IoT spans a broad spectrum of sectors and offers a vast array of functionalities (Jain et al. 2021). These functionalities make IoT a unique technology that enables a wide variety of offerings. Most importantly, the advancements in IoT devices have enabled firms and individuals to produce vast amounts of data, leading to the development of IoT data ecosystems. These ecosystems enable companies to capture, exchange, monetize, and analyze IoT data, enhancing their services and sales (Khezr et al. 2022).

The transformative potential of IoT in enabling diverse offerings and value propositions has driven substantial growth in its adoption and market expansion in recent years. The global IoT market is experiencing rapid growth and is projected to reach US$172.6 billion by 2025 (Falkenreck et al. 2023). The number of IoT-connected devices worldwide is forecast to triple between 2020 and 2030, and the total installed base is projected to reach 30.9 billion units by 2025 (Vailshey 2023). IoT is recognized as a game-changer technology that will play a key role in what is known as the "data economy" (González et al. 2023; Khezr et al. 2022). This is partly because IoT can connect various objects, firms, and systems through networked offerings, infrastructure, and technological architectures. It also enables new business models across a wide range of domains using data as a key asset (Martín et al. 2023). These data, constantly generated by the myriad of sensors embedded in the environment, can be transformed, if smartly processed, into added value, enabling novel monetization strategies (Martín et al. 2023). The use of IoT has enabled a wide spectrum of business models, spanning from individual products with limited IoT add-ons to product-service systems and further to IoT platforms and ecosystems where the performance—or even the data itself—can be traded (Khezr et al. 2022; Leminen et al. 2018; Metallo et al. 2018).

While prior research on information systems (IS) and beyond clearly demonstrates that IoT enables a wide variety of data-driven business models (e.g., Angeles 2019; Baines et al. 2009; Endres et al. 2019; Liu et al. 2020), the growing diversity of such models has also led to increasing conceptual fragmentation. Existing studies often describe IoT-enabled offerings at different levels of analysis, ranging from product-level enhancements (e.g., Boehmer et al. 2020; Jabeen and Ishaq 2023; Oberländer et al. 2018a, b) to platform-based (Muñoz et al. 2020; Rubí and De Lira Gondim 2021) and ecosystem-based configurations (Bansal and Kumar 2020; Woodhead et al. 2018), without offering a unifying perspective on how firms systematically leverage IoT-generated data for value creation and capture. As a result, it remains difficult to compare business models across contexts or to understand how different approaches to data utilization correspond to distinct business models. This fragmentation limits both theoretical accumulation and managerial applicability. This leads to the question: What are the business model archetypes based on IoT data utilization?

2.3 Business model sophistication

The notion of business model sophistication builds on the widely accepted view of business models as interconnected systems of activities that span organizational boundaries and emphasize the creation and capture of value (Amit and Zott 2001; Teece 2010). As firms evolve, their business models progress from simple configurations focused on basic functionality to more interdependent and dynamic systems that leverage digital technologies, customer insights, and networked collaborations. The current literature has a value-centric view of business model sophistication, defining it as a firm's ability to capture value from secondary opportunities beyond its core business. In other words, it involves designing the business model to exploit additional revenue or cost-saving streams that are enabled by—but not part of—the main offering. Kesting and Günzel-Jensen (2015) define business model sophistication as the "realization of secondary value-capturing opportunities beyond the main business" (p. 286), arguing that these opportunities are only made possible by the firm's core offering. Battistella et al. (2021), on the other hand, argue that complex, highly sophisticated business models involve different firms that provide free flows of value to different customers, often with more than one focal firm. Sophistication can also arise from developing complementary products, which can lead to lock-in customers and, consequently, make offerings more complex (Günzel-Jensen and Holm 2015).

In this study, we take a more holistic perspective that considers the foundational changes resulting from the integration of advanced technologies and offering logic.

In this view, the introduction of new services, features, and functionalities significantly impacts both value creation and capture, leading to increased sophistication in business models. This sophistication occurs at varying levels depending on the nature of a firm's core offerings. Research indicates that the integration of advanced technologies or servitization can contribute to the development of more sophisticated business models (Golgeci et al. 2022; Palo et al. 2019; Queiroz et al. 2020). Accordingly, we define business model sophistication as the extent to which a firm's value creation and capture mechanisms incorporate advanced technological capabilities, complex service offerings, and tailored customer solutions to generate superior value. Business model sophistication also reflects the realization of superior value-capturing opportunities (Kesting and Günzel-Jensen 2015). This sophistication is enabled by and facilitates the transition from basic features and functionalities to more advanced, interconnected core offerings that leverage cutting-edge technologies. Key characteristics of sophisticated business models include a deep understanding of customer needs, the ability to provide highly personalized and dynamic services, and continuous innovation in value creation mechanisms. In the context of IoT, this sophistication aligns with the increasing technological complexity of offerings and interconnected devices that operate in tandem. Although prior research acknowledges that business models vary in their level of sophistication (Battistella et al. 2021; Damsgaard 2023; Kesting and Günzel-Jensen 2015; Rupeika-Apoga et al. 2022), existing studies largely treat sophistication as a static, cross-sectional factor. In the context of IoT-enabled business models, the literature offers limited understanding of how firms progress across different levels of business model sophistication, particularly in how IoT data are increasingly embedded in value creation and capture mechanisms. This leads to the question: How do business models advance in sophistication?

3 Methods

To develop and enhance the conceptualization of technology-driven business models, it is essential to draw on a broad spectrum of data. To this end, and to address the research questions, we employed a pluralistic methodological perspective and implemented a multi-method research design. This approach allows us to leverage a variety of methods, and it facilitates an examination of the phenomenon from multiple perspectives (Mühlburger and Krumay 2024; Niehaves 2005). Multi-method research refers to the integration of two or more distinct methodological approaches within a single inquiry to address a unified research goal (Sarker et al. 2013). Unlike traditional single-method designs, multi-method studies deliberately combine diverse approaches to capture the multifaceted nature of contemporary sociotechnical phenomena. Moreover, to prevent ambiguity and confusion arising from redefining the established term "mixed methods," we adopt the term "multi-method" (Hunter and Brewer 2015; Sarker et al. 2013; Wellman et al. 2023), which is a broader concept. This approach has gained prominence in management science, particularly in IS research, due to the increasing complexity and multidimensionality of digital technologies and the proliferation of diverse data sources (Sarker et al. 2013), such as those generated by IoT sensors and IoT-enabled products and services. This complexity necessitates methodological pluralism through multi-method approaches to generate deeper insights, explore complex questions more holistically, and produce integrative inferences that would be unattainable through a singular methodological lens.

This study comprises two qualitative methods implemented sequentially in two distinct phases. In Phase 1, we developed a typology from the academic literature to identify manifestations of IoT business model archetypes and their progression. The resulting framework comprises three archetypes—connectivity, servitization, and data ecosystems—which emerged inductively through open coding of the literature. These archetypes represent patterns of value creation and capture mechanisms rather than a rigid hierarchical classification and, therefore, are best understood as a typology. This typology provides a foundational analytical lens for interpreting progression in business model sophistication. In Phase 2, we extended and enriched this typology by examining its core components of value creation and capture through an empirical study drawing on archival and secondary data. The findings from both phases were subsequently integrated to produce an IoT business model progression framework.

3.1 Systematic literature review

The first step in the research process to address the questions is a systematic review of the existing literature. Literature reviews have become a critical part of scientific research, particularly in management studies (Kraus et al. 2022; Sauer and Seuring 2023), as they play a critical role in keeping up with the latest developments in existing knowledge (Kraus et al. 2024). This type of literature review has become a standard tool in management fields (Sauer and Seuring 2023), as it helps researchers to better understand prior work in their domain, identify gaps in the literature, and highlight promising directions for further exploration (Kraus et al. 2022). It has also been providing a foundation for developing new ideas, theories, and methodologies (Kraus et al. 2024). A systematic review is an organized approach to collecting and analyzing existing literature (Lucas-Alfieri 2015). It applies predefined strategies to reduce bias when identifying and analyzing data from original studies (Barbosa et al. 2019). Therefore, it guides the research process, reveals current trends, highlights the outcomes of previous initiatives, identifies opportunities for future work, and serves as a critical discovery phase (Lucas-Alfieri 2015). Building on Toorajipour's (2025) work, we followed the literature review approach suggested by Denyer and Tranfield (2009) to ensure high quality and robustness. This method has become widely adopted due to its rigorous, transparent, and replicable approach to synthesizing existing research. We employed this approach because of its structured and predefined protocol for literature identification, selection, and analysis, which minimizes researcher bias and ensures the review process is systematic and comprehensive. Such a structured methodology enhances the credibility and reliability of the findings, which is particularly important in heterogeneous studies focusing on technology-driven topics such as IoT business models.

The paper search began in early October 2023, with two subsequent updates conducted in November 2023 and January 2024. The search string was formulated to maximize the inclusion of relevant studies, ensuring a comprehensive review. The search terms used were ("IoT" AND "business model") OR ("Internet of Things" AND "business model"), applied to the titles, abstracts, and keywords of the papers. The initial search was conducted on the Web of Science, yielding a preliminary set of 458 academic papers. To refine the selection and focus on high-quality, relevant research, a filter was applied, restricting results to journal articles in English within the business category. This refinement reduced the pool to 52 papers for the next stage. Further screening excluded papers that lacked a clear focus on IoT business models, resulting in a final set of 35 papers from Web of Science. A parallel search was performed in Scopus using the same search string and criteria, producing an initial pool of 1,714 articles. The results were further refined by restricting the selection to studies explicitly containing "Internet of Things," "IoT," and "business model" in their keywords, reducing the pool to 122 papers, including 20 duplicates. After removing these duplicates, 102 papers remained, which were further screened using the same inclusion criteria as for Web of Science, resulting in a final selection of 50 papers from Scopus.

Following the initial search and filtering conducted within Scopus and Web of Science based on predefined criteria (e.g., language, document type, and subject area), an additional manual screening process was applied to ensure the relevance and quality of the final sample. For both Scopus and Web of Science, the search protocol followed the same logic, and the same set of inclusion and exclusion criteria was applied. Each retrieved article was first assessed by carefully reading its title and abstract to determine whether it explicitly addressed IoT business models. When relevance could not be clearly established at this stage, the full text of the article was reviewed. This screening protocol ensured that only studies with a substantive focus on business models—or on value creation and capture in IoT contexts—were retained.

Papers were excluded if they merely mentioned IoT or IoT business models without offering meaningful theoretical, conceptual, or empirical insights relevant to the objectives of this review. Studies that focused primarily on technical architecture, engineering aspects, or isolated IoT applications, without explicitly considering business model implications, were removed. Therefore, the inclusion criteria required a clear contribution to the understanding of IoT business models. This ensured that the final set of articles directly informed the study's investigation of IoT business model archetypes, thereby enhancing the analytical depth of the review. In total, 85 papers were identified for analysis and synthesis. Figure 1 presents the steps in the literature review process, following Denyer and Tranfield's (2009) approach.

To analyze the collected text, we employed the open coding technique (Seale 2004). This approach served as the first step in our data analysis process, enabling new theoretical insights to address the research questions. Open coding entails the fracturing of raw qualitative data into discrete parts to uncover concepts, categories, and their underlying properties (Strauss and Corbin 1998). The purpose of this process is to move beyond mere description toward a conceptualization of observed phenomena (Strauss and Corbin 1998)—in this study, the business model archetypes. In the context of IoT business models, open coding is particularly useful as it enables

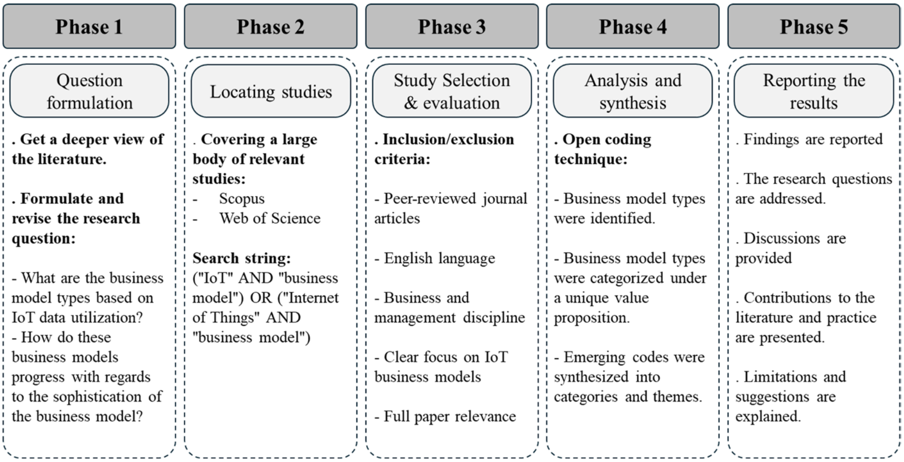

Fig. 1 Systematic literature review process

the discovery of novel patterns and relationships across a diverse set of materials, such as the academic literature.

To this end, the content of each paper (from the literature review) was meticulously explored. Coding was conducted with the aim of identifying the business model archetypes. During open coding, authors engaged in line-by-line analysis of raw qualitative data, carefully examining the text from the papers drawn from the systematic literature review. Each segment of data was scrutinized for evidence related to business models, and this evidence was then labeled with conceptual codes. These served as provisional labels for codes and patterns that emerged from the data. As Strauss and Corbin (1998) argue, this inductive approach ensures that the developing analysis remains grounded in empirical evidence, rather than being constrained by pre-existing notions. Emerging codes were then synthesized into categories and themes based on the unique value propositions they represented. A key activity in our open coding was the constant comparison of data segments to identify similarities, differences, and variations. Through this process, we refined the codes and grouped related codes into broader categories. Each category was further elaborated by identifying its properties, allowing for a richer and deeper understanding of the phenomenon under study.

The outcome of open coding was a set of emergent business model archetypes linked to a unique core value proposition that captures the core idea of that specific archetype. As a result, three business model archetypes were identified, reflecting the empirical view of the field while providing the foundation for the subsequent stage—the empirical case study. By systematically applying open coding, we ensured that the findings on IoT business models remain both empirically grounded and analytically robust, while capable of capturing the complexity and dynamism inherent in the IoT-based businesses.

To structure the identified business model archetypes into a progression framework, we assessed their relative sophistication, which is conceptualized as the degree to which value creation and capture mechanisms incorporate advanced technological capabilities, complex service components, and tailored customer solutions. Drawing on this conceptualization, we sorted the three business model archetypes along a sophistication continuum. The logic underpinning this ordering is based on three dimensions. First, technological complexity, which is the extent to which IoT capabilities, such as real-time data collection and analytics, remote control, and automation, are embedded in the model. Second, service orientation and customization refer to the degree to which the offering can shift from stand-alone products to integrated products and services that address more complex needs. Third, network embeddedness refers to the level of inter-organizational collaboration and data sharing, reflecting a move from single-firm value creation to multi-actor ecosystems. Based on these dimensions, connectivity models represent the entry point of sophistication. Servitization models build on connectivity by incorporating service-based value propositions and consequently enhancing value capture capacity. Finally, data ecosystem models represent the highest level of sophistication, in which multiple actors co-create value by leveraging data. Organizing the typology along this trajectory provides not only an analytical lens for interpreting observed cases but also a framework for assessing strategic positioning in IoT-driven industries. In addition, the papers corresponding to each business model archetype were identified and categorized (see Table 2 in the Results section).

3.2 Empirical study

To explore the details of IoT business model archetypes—particularly, value creation and capture—we relied on empirical data from archival and secondary sources. We utilized a multiple case study approach and identified relevant IoT companies as cases. We grouped them according to the IoT business model archetypes identified from the systematic literature review, collected and analyzed data for each case, and provided details on value creation and capture components. This empirical data collection phase was designed as the second stage of a multi-method research design (Sarker et al. 2013), directly building on the typology developed in the systematic literature review. The review provided conceptual archetypes and offered preliminary insights into the progression of business model sophistication. The case study phase extended this foundation by empirically validating and enriching these archetypes, allowing for greater granularity and contextual understanding of how value creation and capture mechanisms manifest in practice. This sequential design was employed to enhance theoretical grounding from literature while also enabling empirical refinement.

4 Research design: multiple case study

A multiple case study design (Yin 2009) was utilized to examine the business models of the IoT companies. Case study research has been widely used across various domains to develop an understanding of phenomena in their natural settings (Krohn 2017). It is also the most widely used qualitative research method in the information systems research community (Orlikowski and Baroudi 1991). A case study is an empirical inquiry that examines a contemporary phenomenon in its real-life context, particularly when the boundaries between the phenomenon and its context are not clearly defined (Yin 1994). This is relevant to this study, as a business model is deeply embedded in a company's fabric—particularly in its structures, operations, strategies, and routines. In this study, each company represents a case, and the embedded units of analysis (Yin 2009) are the business model components (value proposition, creation, and capture). This design is particularly suited to this research because it allows for a detailed, comparative, and contextually rich analysis of IoT business models, facilitates theory development, and provides valuable insights for both the academic audience and practitioners.

4.1 Case selection and data collection

Following the logic of multi-method research (Niehaves 2005; Sarker et al. 2013), the case study phase was designed to complement and expand the conceptual framework developed through the systematic literature review and provide empirical grounding for the progression framework. Fourteen companies were selected: Gardena, Grundfos, John Deere, Carrier, Hilti, Kone, Michelin, Telenor, Sandvik, NetAtmo, Velux, Bosch, KPN, and Schneider Electric. The cases were selected using theoretical sampling (Eisenhardt 1989; Strauss and Corbin 1998) to ensure that the selected companies reflect the diversity of IoT business model archetypes, provide sufficiently rich data for analysis, while remaining analytically comparable and rigorous. In theoretical sampling, cases or data sources are selected to develop and refine emerging theoretical categories (Charmaz 2001). This approach strengthens the analytical framework by progressively enhancing the precision, richness, and complexity of the theoretical statements while firmly grounding them in empirical data (Charmaz 2001). Eisenhardt and Graebner (2007) argue against random or convenience sampling of cases when the aim is to develop theory. Instead, they advocate selecting cases for their potential to contribute to or extend emerging theory. Through iterative engagement with the data, theoretical sampling enabled us to focus on areas most likely to yield insights into the core categories of the evolving theory and, in doing so, facilitated the analysis's elevation to a more abstract and conceptually sophisticated level (Charmaz 2001). Table 1 provides an overview of the case companies and summarizes key descriptive details, including industry, firm size, geographic scope, and assigned business model archetype.

Theoretical sampling also facilitates bias minimization. Wiesche et al. (2017) note that theoretical sampling tends to increase the credibility of studies by expanding data coverage. They argue that "theoretical sampling reduces sampling bias and increases data coverage and the saturation of categories" (p. 688). In other words, by iterating between data collection and analysis and following where the emerging theory leads, researchers can mitigate sampling bias, as this approach is less likely to overlook important variations that a fixed sampling strategy might miss. Moreover, Birks et al. (2013) view theoretical sampling as a means to avoid bias and achieve adequate variation in data, explaining that "Theoretical sampling also helps reduce sampling bias and insufficient variation in data, while maintaining focus on the researcher's goals" (p. 3).

Table 1 Descriptive details of the case companies

Company	Primary industry	Firm size	Geographic scope	Business model type
Gardena	Gardening tools and equipment	SME	Europe	Connectivity
Grundfos	Water technology and pumps	Large	Global	Connectivity
John Deere	Manufacturer of agricultural and construction machinery	Large	Global	Connectivity
Carrier	HVAC systems and temperature management	Large	Global	Connectivity
Hilti	Construction tools and services	Large	Global	Servitization
Kone	Elevator engineering company	Large	Global	Servitization
Michelin	Tyre manufacturer	Large	Global	Servitization
Telenor	Telecom and connectivity services	Large	Global	Servitization
Sandvik	Industrial manufacturing	Large	Global	Servitization
NetAtmo	Consumer IoT devices	SME	Global	Data Ecosystem
Velux	Building products and smart solutions	Large	Global	Data Ecosystem
Bosch	Engineering, IoT, and consumer tech	Large	Global	Data Ecosystem
KPN	Telecom and IoT connectivity services	Large	Europe	Data Ecosystem
Schneider Electric	Industrial electronics and automation	Large	Global	Data Ecosystem

To minimize bias, particularly confirmation bias, we implemented the following measures. First, we selected multiple cases rather than a single case. Eisenhardt (1989) advocates using multiple cases over single-case studies because this strengthens findings through comparison across cases. Next, we established a set of predefined and transparent inclusion and exclusion criteria before sampling began (Coyne 1997; Sandelowski et al. 1992). We made these criteria explicit to ensure replicability and prevent ad hoc decisions influenced by researchers' expectations. Thus, the cases were selected on the basis of four criteria. First, the company must utilize IoT in its core offering to enhance value for its intended customers. This excludes companies that use IoT for other purposes, such as in production processes, facilities, and buildings. Moreover, companies that produce IoT devices as a final product (vendors of IoT components or suppliers of IoT devices) are excluded. The second criterion is the strategic use of IoT. This means that the IoT technology is regarded as a strategically important component of the selected companies' business models and is reflected in their value proposition. Third, the company must be an established company with a clear track record of offerings based on IoT technology. This excludes startups or young companies without a firm presence in the marketplace. Finally, the last criterion is the availability of data on the company's use of IoT technology and its business model, which can serve as a source of data collection in our research. We followed the above four criteria as the main logic and filter for choosing the cases, rather than specific industry or firm size, as the aim was to identify the cases that best contribute to theory development. Moreover, the geographical scope of the sample was intentionally global to allow flexibility in the selection of cases. Furthermore, we relied on independent screening and multiple investigators to compare independent insights, which can significantly reduce individual biases in interpreting data. As suggested by Eisenhardt (1989), multiple researchers independently assessed cases against the criteria. Finally, we utilized multiple forms of data such as blogs, catalogs, brochures, and newsletters to enhance validity and achieve data source triangulation (Eisenhardt and Graebner 2007). Pioneers of works on qualitative rigor, such as Miles and Huberman (1994) and Patton (2014), regard triangulation as a critical aspect of unbiased research.

For each company, we systematically gathered multi-format archival materials comprising textual and visual data. It is recommended that a case study analysis should use all relevant evidence (Rowley 2002). Therefore, relevant data were collected from company websites, blogs, catalogues, newsletters, corporate reports, product brochures, and white papers (e.g., Damsgaard 2023). These data sources were chosen for two main reasons. First, our research objective required comprehensive and multifaceted evidence covering the business model details and IoT use. Archival data are particularly suited to case studies, as they provide rich, real-world context and enable analysis of the phenomena (Yin 2009). Second, using non-intrusive data sources facilitated the inclusion of unique, rich, and irreplaceable material (Calantone and Vickery 2010; Yin 2015) while mitigating respondent bias arising from self-reported data in interviews or surveys.

Data collection followed a protocol to ensure rigor and replicability. Initially, potential sources were identified and screened to ensure relevance and adequacy. Subsequently, documents were archived and organized in a structured database, with metadata detailing source type, date, and company association. To maintain consistency among researchers, we developed and adhered to a data collection protocol that specified source types and retrieval procedures, as proposed by Yin (2015). Periodic cross-checks and peer reviews were conducted to ensure completeness and accuracy, and missing or ambiguous information was supplemented with additional material. Moreover, several measures were implemented to enhance data quality and researcher objectivity. Triangulation across heterogeneous sources was applied to validate key findings and reduce overreliance on single data types (Eisenhardt and Graebner 2007). Peer debriefings were conducted throughout the process to challenge interpretations and mitigate confirmation bias (Charmaz 2001). The data collection process resulted in a corpus of over 700 pages of content, organized by company, forming the empirical foundation for subsequent coding and comparative analysis of value creation and capture mechanisms across the identified IoT business model archetypes.

4.2 Data analysis

Since this study employs an exploratory research approach based on multiple case study design, we adhere to a general strategy of working our data from the ground up as recommended by Yin (2009). Overall, we looked for patterns, ideas, concepts, and insights using methods such as creating data displays and organizing information into arrays and structures (Miles and Huberman 1994). The analysis process involved several steps to categorize and interpret the data effectively. Initially, each company's business model was analyzed individually. Case companies were grouped according to their core value propositions. Companies representing the first group included Gardena, Grundfos, John Deere, and Carrier; companies representing the second group included Hilti, Kone, Michelin, Telenor, Sandvik; and companies representing the third group included NetAtmo, Velux, Bosch, KPN, and Schneider Electric. Figure 2 shows three groups of case companies based on the sophistication of their IoT business models.

This stratified approach provided a more structured path for the next step—a comprehensive examination of the other business model components across the case companies. The data for each group were then coded and categorized using thematic analysis to identify value-creation and capture mechanisms. We followed the thematic coding approach of Miles and Huberman (1994). We employed an interactive and iterative process involving three concurrent activities: data reduction, data display, and conclusion drawing. These activities were repeated and overlapped

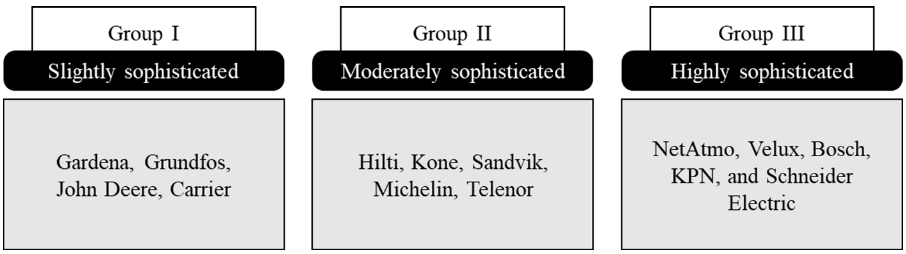

Fig. 2 The three groups of case companies

throughout the process, allowing us to distill meaningful themes and patterns from raw textual data. Moreover, to enhance analytical rigor, several researchers were involved in the coding process (Guest et al. 2011; Saldaña and Omasta 2016). An initial coding framework was developed based on the research questions and iteratively refined through repeated engagement with the data (Braun and Clarke 2006; Saldaña and Omasta 2016). Coding was conducted independently, and intercoder consistency was assessed through systematic comparison and discussion of the coding outcomes (Guest et al. 2011; Saldaña and Omasta 2016). Discrepancies were resolved through consensus, contributing to a robust and reliable interpretation of the data.

Data reduction was primarily intended to simplify the raw data and extract what was relevant to the research question and, more particularly, the business model archetypes. Data reduction was conducted by summarizing documents, coding text segments, identifying patterns, and clustering them. This was done for each business model archetype, using data from companies in that group (see Fig. 2). Coding the data is considered the primary technique for data reduction in thematic analysis (Miles and Huberman 1994). Before coding the raw data, we read and re-read the documents to grasp the core ideas and understand their context and content. Coding had two main cycles. In the first cycle, we broke the text into meaningful segments and assigned descriptive codes related to the business model concept. We systematically labeled text segments—from single words to complete paragraphs—with codes representing concepts or categories. As (Miles and Huberman 1994) suggest, we began with an initial set of codes derived from research questions and a conceptual foundation from the systematic literature review. The second cycle focused on iterative refinement and revision of the codes. Here, we reviewed codes to exclude redundancies, split overly broad codes, and identified emerging patterns. We then grouped these codes into more general themes.

Following data reduction, the next step was data display. We organized the codes and themes using visual and textual elements in preparation for the analysis. Following Miles and Huberman (1994), we assembled the available codes and themes into an accessible and compact form to facilitate conclusion drawing. Here, the goal was to transform a mass of coded text into a structured, interpretable format. At this stage, we structured the second-order business model subcomponents—such as data-driven functionality, X-as-a-service, upgradability, optimization, and new markets—into coherent components. By carefully selecting representative subcomponents and arranging them into thematic categories (business model components), we were able to create a visual overview of the empirical evidence (see Fig. 3).

The third activity was to draw conclusions by striving to make sense of the themes and determining their meaning in the context of IoT business model archetypes and their progression. Through careful analysis and continuous verification of the themes, we solidified them into well-founded conclusions and consolidated business model archetypes. We articulated what each theme signified and how they relate to one another to answer the main research question. We also linked the themes to the theoretical foundation from the literature review to facilitate interpretation. During the data analysis and synthesis, particular emphasis was placed on researcher objectivity by consistently anchoring the analytical process to the research questions to minimize bias (Holton and Walsh 2016; Kane et al. 2025). The analysis helped us to compare

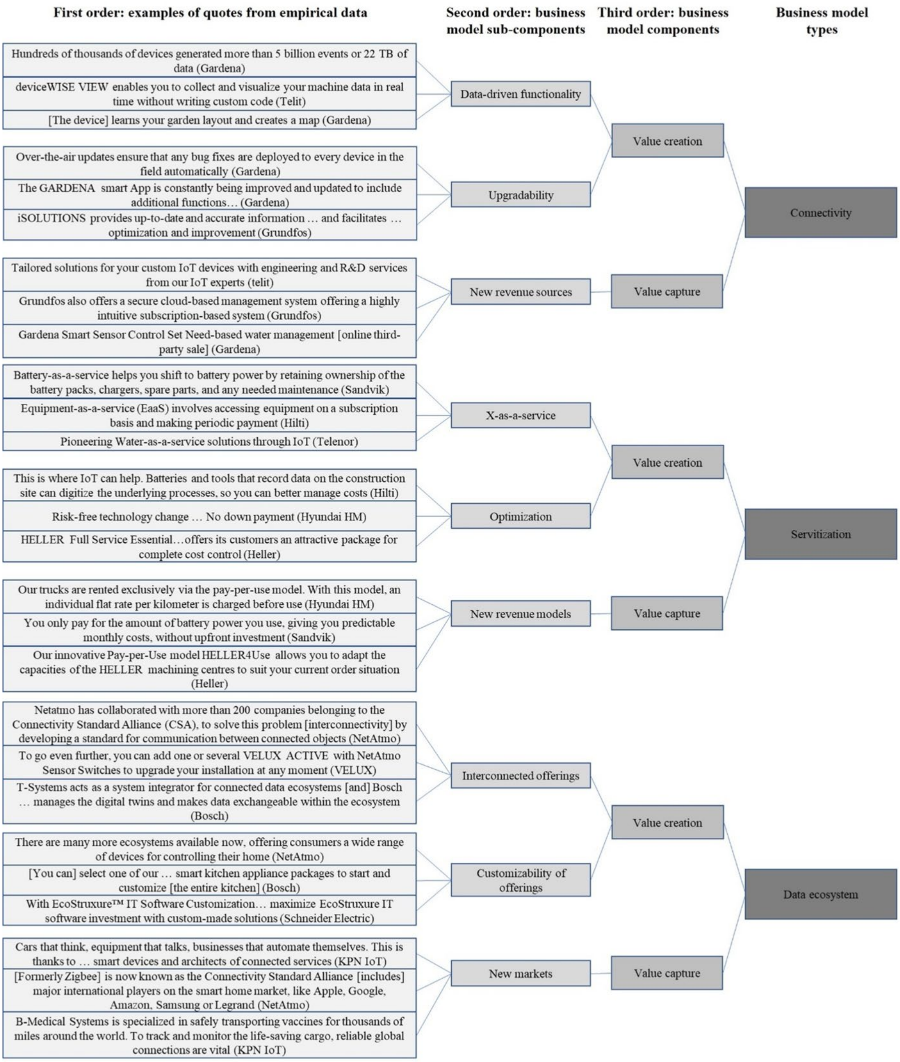

Fig. 3 The thematic coding of the data, from quotations to themes and patterns

and contrast business model components across different groups. The first-, second-, and third-order themes and patterns are shown in Fig. 3.

5 Results

The analysis and synthesis of data from the systematic literature review resulted in the identification of three IoT business model archetypes (connectivity, servitization, and data ecosystem) centered around a unique value proposition. The literature review also revealed a pattern that represented business model sophistication and progression. For each archetype, the components of value creation and capture were identified from the case study through a systematic comparison of how firms leverage IoT technology and IoT-generated data. Across cases, differences were not merely driven by industry or technology choice but by the role of data within the business model logic. Findings suggest that each of these IoT business model archetypes is distinguished by its core offering idea.

In the first group, namely connectivity, IoT data were predominantly used to support core product functionality and operational efficiency. Connectivity-based business models primarily focus on enabling communication between devices, users, and platforms, supporting basic data transmission and providing fundamental IoT functionalities. In this category, value creation is centered on enhanced product performance and reliability. Value capture mechanisms remain closely tied to traditional product sales or connectivity-based revenues, indicating a limited extension beyond the core offering.

Servitization business models shift from product-centric approaches to service-based solutions and leverage IoT to deliver continuous value through new revenue models. This business model archetype was characterized by a deeper integration of IoT data into service-based value propositions. Here, firms leverage data to enable advanced services such as predictive maintenance, optimization, and performance-based offerings. Value creation shifted from data-driven functionalities and upgradability toward continuous service provision and customer problem-solving, often through subscription or outcome-based pricing models. This archetype represents a higher level of business model sophistication, with data serving as a central resource for offerings and sustaining long-term customer relationships.

The third archetype, the data ecosystem business model, was distinguished by the strategic use of IoT data beyond firm boundaries. This represents the most sophisticated archetype, integrating diverse actors in a collaborative network where IoT-generated data is shared, processed, and monetized. Here, value creation relied on aggregating and sharing data, forming interconnected offerings, and providing customizability. Value capture also extended beyond new revenue sources or revenue models to include new markets.

In addition to identifying distinct business model archetypes, the systematic literature review revealed a pattern of business model sophistication and progression. As IoT adoption matures, business models tend to evolve in complexity, moving from basic connectivity-based offerings to more integrated and data-driven ecosystems. This progression reflects an increasing level of technological capability, strategic integration, and value co-creation. As explained previously, business model sophistication in this study refers to the extent to which a firm's value creation and capture mechanisms integrate advanced technological capabilities, complex service offerings, and customized customer solutions to enhance value generation. This sophistication emerges from moving beyond simple functions to more integrated, technology-driven solutions that leverage state-of-the-art technologies. Connectivity-based models represent the most fundamental level, providing essential IoT functionalities but offering limited differentiation beyond device connectivity. Servitization introduces higher sophistication by incorporating service-driven revenue models, increasing customer engagement, and operational efficiency. The data ecosystem model represents the most sophisticated archetype, where various firms collaborate to exchange, analyze, and commercialize IoT-generated data, creating a networked environment of continuous value innovation. This hierarchy of sophistication was derived from patterns observed in the literature, where business models exhibiting greater integration of IoT functionalities and data-driven capabilities were positioned at higher levels of sophistication. By synthesizing these insights, the systematic literature review offers a structured perspective on how IoT business models progress, presenting both a typology of business model archetypes and a framework for understanding their progression trajectory. Table 2 presents the three business model archetypes along with the corresponding papers from the systematic literature review.

Table 2 Business model archetypes and the corresponding papers from the literature review

	Web of science	Scopus
Data ecosystem	Wan et al. (2014), Warner and Wäger (2019), Leminen et al. (2018), Metallo et al. (2018), Hanafizadeh et al. (2021), Abbate et al. (2019), Nguyen Dang Tuan et al. (2019), Paiola et al. (2021), Hasselblatt et al. (2018), Matthyssens (2019), Leminen et al. (2018), Paiola et al. (2022), Cranmer et al. (2022), Ehret and Wirtz (2017), Leminen et al. (2020), Gebauer et al. (2020), Paiola and Gebauer (2020), Radenković et al. (2020), Şimşek et al. (2022)	Ancillai et al. (2023), Garbuio and Gheno (2023), Saarikko et al. (2017), Almeida et al. (2020), Hamidi and Jahanshahifard (2018), Hashem et al. (2016), Laya et al. (2018), Ulrich et al. (2023), Delgosha et al. (2022), Del Sarto et al. (2022), Abdelghaffar and Abousteit (2021), Niyawanont (2022), Kraft et al. (2021), Chen et al. (2021), Marcon et al. (2022), Leminen et al. (2017), Wielki (2017), Volberda et al. (2021), Mahdad et al. (2022), Leiting et al. (2022)
Servitization	Leminen et al. (2018), Metallo et al. (2018), Hanafizadeh et al. (2021), Naik et al. (2020), Straker et al. (2021), Ge et al. (2016), Veile et al. (2022), Park et al. (2023), Le et al. (2019), Hasselblatt et al. (2018), Matthyssens (2019), Leminen et al. (2020), Abbate et al. (2019), Nguyen Dang Tuan et al. (2019), Sturm et al. (2023), Foltean and Glovatchi (2021), Shoukry et al. (2021), Paiola et al. (2022), Cranmer et al. (2022), Haaker et al. (2021), Paiola and Gebauer (2020), Paiola et al. (2021)	Athanasopoulou et al. (2019), Saarikko et al. (2017), Esmaeilpour Ghouchani et al. (2019), Boehmer et al. (2020), Almeida et al. (2020), Ulrich et al. (2023), Lee (2019), Giovanardi et al. (2023), Lai et al. (2017), Krotov (2017), Molling and Zanela Klein (2022), Ammirato et al. (2022), Delgosha et al. (2022), Marcon et al. (2022), K.-L. Chen et al. (2023), Rocha et al. (2022), Hashem et al. (2016), X. Zhang et al. (2022), Gao and Li (2020), Weking et al. (2020), Palmaccio et al. (2021), Volberda et al. (2021), Liu et al. (2020), Del Sarto et al. (2022), Hamidi and Jahanshahifard (2018), Hakanen and Rajala (2018), Lokshina et al. (2018), Alcayaga et al. (2019)
Connectivity	Abbate et al. (2019), Kaur and Kaur (2018), Falkenreck et al. (2023), Gebauer et al. (2020), Ge et al. (2016), Foltean and Glovatchi (2021), Yopan et al. (2022), Ehret and Wirtz (2017), Shoukry et al. (2021), Matthyssens (2019), Straker et al., (2021), Haaker et al., (2021), Paiola and Gebauer, (2020), Zancul et al., (2016), Passlick et al., (2021), Barrar and Ruiz-Benitez, (2023)	Lamendola and Genet (2022), Weking et al. (2020), Almeida et al. (2020), Mattos and Novais Filho (2023), Saarikko et al. (2017), Esmaeilpour Ghouchani et al. (2019), Qiu et al. (2015), Mattera and Gava (2022), Angeles (2019), Kraft et al. (2021), Leiting et al. (2022), Chauhan et al. (2022), Palmaccio et al. (2021), Njomane and Telukdarie (2022), Abdelghaffar and Abousteit, (2021), Kiel et al. (2017), Z. Zhang et al. (2023), Nalajala et al. (2023), Wielki (2017), Sood and Woodside (2021), Karttunen et al. (2021)

The systematic literature review, as well as the empirical study of fourteen IoT companies, led to the identification of the three business model archetypes, including value creation and capture components for each archetype. The empirical analysis allowed for a more nuanced understanding of how firms operationalize their IoT business models and the mechanisms through which they generate and capture value. In the following section, the three business model archetypes and their components are explained.

5.1 Archetype I: connectivity

IoT provides the infrastructure for the information networks that enable enhanced offerings by connecting physical and virtual objects. According to our findings, connectivity is the most fundamental IoT business model archetype. IoT enables connectivity between devices and between devices and users. IoT technology transforms the way devices communicate and interact, establishing a robust infrastructure for connectivity. IoT enables direct communication between devices, allowing them to exchange data and coordinate actions autonomously. Devices can also send data to centralized cloud platforms, where it is processed, analyzed, and stored. This enables deeper data analytics and the implementation of algorithms that provide actionable insights. In some cases, IoT devices communicate with intermediary gateway devices that aggregate data from multiple sources before sending it to the cloud. This approach is useful in scenarios where low-latency communication or local processing is required, as in smart agriculture, where sensors collect soil moisture and weather data for immediate local analysis and action. Moreover, IoT enables interaction between objects (such as IoT-enabled products) and users by providing real-time insights, analyses, and notifications through software applications and other digital user interfaces. IoT devices continuously collect data, which can be instantly processed and displayed to the users. They can send timely notifications and alerts to users about ongoing events or unpredictable conditions. IoT also enables automated actions based on data-driven insights.

Our findings show two value creation components for this business model archetype. The first is data-driven functionality, through which value is created by using IoT to enhance the functionality of products based on data from connected devices. These data can be used to improve performance, offer new features, provide data-driven insights, and provide personalized experiences and add-ons. The second value-creation component is upgradability. IoT allows products to be continuously upgraded and improved through software updates and new features. This transforms traditionally static products into dynamic ones that evolve continuously. This allows users to obtain the features and add-ons they require without changing the product or buying new hardware or software. The two value creation components, while providing new possibilities and benefits for the customers, enable companies to capture value from new sources that were not previously accessible without IoT. Companies can capture value in innovative ways, such as through subscriptions for specific added services, which provide a steady revenue stream. Moreover, companies can monetize additional add-ons and upgrades that enhance the functionality of their IoT-enabled products. IoT connectivity also allows companies to offer consultation, maintenance, and support services as part of a service contract. This model not only generates recurring revenue but also builds long-term customer relationships by ensuring up-to-date functionality and ongoing optimization of connected products.

5.2 Archetype II: servitization

The next IoT business model archetype is called servitization. Servitization refers to the transformation of a company's capabilities and strategy from selling products to providing comprehensive solutions that include services. This can involve product-service systems (PSSs) and fully servitized products. A PSS is a business model where products and services are integrated into an offering designed to deliver specific value to the customer. PSSs are often seen as a subset or precursor of fully servitized products, which focus on creating and delivering a combined product-service package to meet customer needs through a mix of tangible products and intangible services. This can enhance the functionality and value of offerings for users. Servitized products refer to a business model in which the company retains ownership of the product and just sells the customer the right to use it. IoT can play a vital role in enabling servitization by integrating sensors, connectivity, and data analytics into products, transforming them into intelligent, connected devices. These IoT-enabled devices can collect and transmit data, allowing companies to offer advanced services that go beyond traditional product offerings. This integration allows businesses to deliver enhanced value to customers through continuous monitoring, real-time analytics, and predictive maintenance. IoT enables product–service systems by providing the infrastructure for real-time data collection and analysis. Connected devices equipped with IoT sensors can monitor their performance and usage, transmitting these data to databases where they can be analyzed to provide insights and trigger automated responses.

Our findings reveal two value-creation components for this business model archetype. The first is X-as-a-Service, also referred to as "Everything as a Service". This value creation is rooted in servitization, enabling customers to access and use products through recurring subscriptions instead of making a one-time purchase. It enhances flexibility and scalability, allowing customers to adapt their usage based on their needs, paying only for what they use. It also reduces capital expenditure by shifting from ownership to access. Customers can avoid significant capital investment in equipment. This component allows continuous improvements, as IoT-enabled PSSs can continuously evolve from software updates and new features, ensuring that customers always have the latest capabilities. The second value creation component is optimization, which refers to the ability of IoT-based products and services to help users maximize value and reduce costs by providing detailed insights and analytics. This component can lead to improved product utilization. IoT devices can provide insights into usage patterns and user behavior; they can employ statistics to help customers avoid purchasing products that have limited utility and focus instead on items that deliver the best value. As a result, improved utility can deliver significant cost reductions. Using IoT data to improve efficiency and reduce unnecessary investments can lead to significant cost savings, helping users move to an asset-light approach that relies on service providers for equipment and technology needs and minimizes the need for heavy capital investments. The value capture component in this business model archetype is centered on servitized products and PSSs. It includes, among others, subscription fees, which are recurring payments for access to IoT-enabled services; usage-based pricing, which allows customers to pay according to their actual use; and add-on services, where companies offer additional features such as extended warranties, enhanced security features, and premium analytics packages.

5.3 Archetype III: data ecosystem

The third IoT business model archetype is the data ecosystem. In essence, IoT comprises networks of physical objects embedded with sensors, software, and other technologies to collect and exchange data with other devices and systems over the Internet. This interconnectivity allows devices to function cohesively within a larger ecosystem, facilitating data circulation as well as supporting various applications and services. A data ecosystem enabled by IoT refers to a network of interconnected objects, devices, and systems that communicate and collaborate to create, share, and utilize data. IoT plays a key role in enabling these ecosystems by integrating various devices and sensors, facilitating real-time data exchange and collaborative functionality. These ecosystems are characterized by their ability to aggregate data from multiple sources, analyze them, and provide new possibilities across different platforms and stakeholders. IoT enables networks of interconnected objects and devices by leveraging advanced connectivity technologies, which allow data to be transmitted seamlessly and reliably over long distances and support complex interactions between different systems. IoT-based data ecosystems add substantial value to offerings by enhancing the functionality of core products, and their user experience. They can enable integrated solutions by connecting various devices to address complex problems more effectively. For instance, in healthcare, IoT can link wearable health monitors with hospital information systems, enabling continuous patient monitoring and timely interventions. These data ecosystems can lead to enhanced decision making. The flow of data within an ecosystem allows for real-time analytics and informed decision making as well as performance optimization, improved customer experiences, and the development of new offerings. IoT can also provide increased efficiency and automation. Data ecosystems enable high levels of automation and operational efficiency. Automated processes driven by real-time data can reduce human intervention, minimize errors, and increase productivity.

Our findings reveal two value-creation components for this business model archetype. Interconnected offerings refer to the collaborative development of products and services by two or more companies, resulting in greater combined value than each company could achieve individually. This collaboration leverages the strengths and capabilities of each company to create a more comprehensive solution. The second value-creation component is the customizability of offerings, which enables customers to modify and personalize IoT-based products and services within a data ecosystem to meet their specific needs and preferences. This flexibility is achieved by allowing customers to select and configure different components, both hardware and software, to create a tailored solution, which the complex nature of IoT data ecosystems makes possible. In this business model archetype, the value-capture component

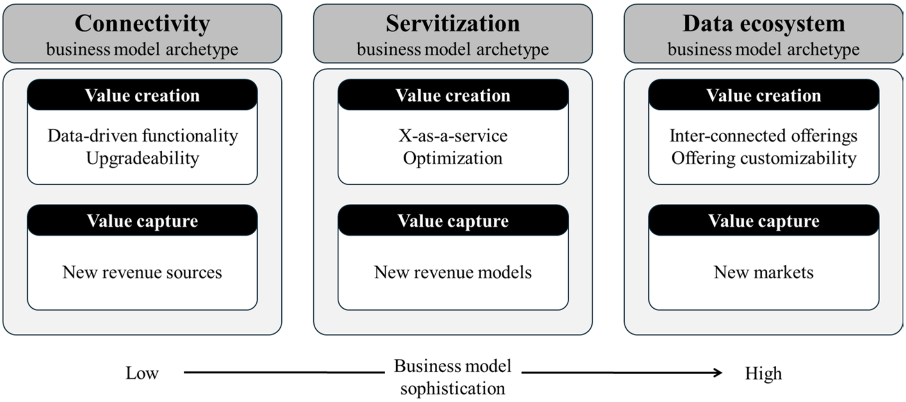

Fig. 4 The IoT business model progression framework

is referred to as new markets. New markets denote companies' ability to access customers and untapped markets that would be difficult to reach without participation in a data ecosystem. Closely related to the value-creation components in this business model archetype, interconnected offerings enable companies to access the customers of their partner company with whom they are developing the offering. Thus, customers can benefit from more sophisticated and customizable offerings, while companies can sell to new customers. Figure 4 depicts the IoT business model archetype framework.

6 Discussion and conclusions

6.1 Study overview and addressing research questions

The current study identifies IoT business model archetypes and their varying levels of sophistication, providing a typology that contributes to both literature and practice. By conducting a systematic review of the literature and a multiple-case study, three distinct archetypes of IoT business models are identified: connectivity, servitization, and data ecosystems. The findings provide a basis for positing a framework of IoT business model archetypes based on the progression of IoT-enabled offerings, along with the value-creation and value-capture components for each archetype. The connectivity archetype focuses on basic data collection and remote monitoring, enhancing product functionality and upgradability. The servitization archetype encompasses PSSs and servitized products that offer flexible, scalable solutions and cost optimization. The data ecosystem archetype represents a highly sophisticated business model, where interconnected devices and systems create collaborative, customizable offerings and open new markets. Although these business model archetypes are conceptually distinct, they are also interconnected. Firms may transition between these models or incorporate elements from several archetypes as they refine their IoT strategies. For instance, a company initially adopting a connectivity-based model may later evolve toward servitization by offering IoT-enabled services and ultimately transition to a data ecosystem model by leveraging network effects and multi-stakeholder data-sharing frameworks. The relationships between these models indicate that IoT business models are not static but can evolve dynamically in response to technological advances and market demands.

Moreover, the findings reveal important contextual patterns that help characterize the three IoT business model archetypes identified. Companies with connectivity business models (Gardena, Grundfos, John Deere, Carrier) are predominantly found among established manufacturing firms whose core offerings remain product centric. These firms use IoT primarily to enhance product functionality through monitoring, control, and basic data-driven features. Across these cases, IoT data is embedded in existing offerings rather than treated as an independent strategic asset. This suggests that the connectivity archetype represents an incremental extension of established business logic rather than a fundamental transformation. Case companies employing the servitization business model archetype (Hilti, Kone, Michelin, Telenor, Sandvik) operate mainly in capital-intensive industrial and infrastructure-related sectors, where long asset lifecycles and performance reliability are important. In these contexts, IoT technology and IoT-driven data play key roles in enabling advanced services such as predictive maintenance and performance optimization. Companies utilizing the data ecosystem business model archetype (NetAtmo, Velux, Bosch, KPN, Schneider Electric) are primarily associated with firms that operate across multiple markets and technological domains. They typically have the organizational capabilities to orchestrate complex, multi-actor environments. These companies extend IoT usage beyond bilateral firm-customer relationships by enabling interconnected offerings and customizability.

The first research question is addressed by systematically exploring IoT business models in the prior literature and empirical cases, which led to identifying three distinct archetypes that reflect fundamentally different logics of value creation and value capture. Rather than classifying firms by industry or technology alone, our analysis focuses on the role of IoT technology and IoT-driven data in the business model archetypes. The second research question is addressed by examining how these archetypes differ in their structural complexity and by interpreting them as representing progressively higher levels of business model sophistication. Our study reveals how increased sophistication is associated with deeper integration of IoT data into value propositions, expanded service orientation, and broader ecosystem engagement.

It is important to clarify that the progression from connectivity to servitization and ultimately to data ecosystems should not be interpreted as a strictly linear or sequential pathway. While the archetypes reflect increasing levels of business model sophistication, firms may follow non-linear trajectories depending on their strategic priorities, customer demands, industry context, and technological capabilities. In practice, organizations may adopt hybrid configurations that combine elements from several archetypes or selectively advance along specific dimensions without completely transitioning to a specific model. Furthermore, although advanced servitization and early-stage data ecosystem configurations may appear conceptually close, they differ in the structural logic underpinning value creation and value capture, as well as in their technological complexity. Advanced servitization primarily extends bilateral firm-customer relationships through data-enabled services and outcome-based offerings, whereas data ecosystem models introduce multi-actor coordination, shared data infrastructures, and complex governance mechanisms that transcend dyadic exchanges. The defining distinction therefore lies not solely in the intensity of data utilization but also in the scope of actor involvement and the redistribution of value creation across a broader network.

6.2 Theoretical contributions

The current study contributes to three streams of conversation in the existing literature. The first contribution is adding a new perspective to the nascent yet growing conversation on IoT business models by offering a typology that not only categorizes these models but also articulates their progression toward higher sophistication. Previous research has provided important classifications and frameworks, such as Leminen et al. (2018) who identify four archetypes of IoT business models—namely, value chain efficiency, industry collaboration, horizontal market, and platform. Similarly, Endres et al. (2019) identify industrial IoT (IIoT) archetypes and their corresponding business model elements, offering insights into IIoT business models in practice by revealing different business model archetypes, including IIoT digical, IIoT service-centered, IIoT data-driven, and IIoT platform. Almeida et al. (2020) use modular business model canvases to primarily identify static patterns or building blocks of IoT configurations. Haaker et al. (2021) provide insights into emerging IoT business models by identifying and interpreting business model design options and choices. Cranmer et al. (2022) explore barriers and factors influencing an organization's ability to implement IoT and suggest a framework to guide organizations in adopting IoT for value creation. While these studies clarify the variety of IoT-enabled business models, they do not capture how such models evolve over time or how their value propositions become more sophisticated as data assets grow and ecosystemic relationships intensify. The typology and progression framework developed in the present study addresses this shortcoming by conceptualizing IoT business models as dynamic configurations that advance from basic connectivity to service orientation and finally toward data ecosystems. It also highlights the critical role of technological maturity, data availability, and business networks in IoT business model evolution.

In doing so, this work responds to calls in the literature for frameworks that integrate technological, managerial, and ecosystem perspectives in IoT contexts (Almeida et al. 2020; Endres et al. 2019; Kohtamäki et al. 2024). Baiyere et al. (2020) and Cranmer et al. (2022) point to the fragmentation of IoT business model research and the need for comprehensive frameworks that bridge technology-centric and value-centric views, as well as the need to examine how firms can build effective strategies to gain value from IoT. By combining insights from a systematic literature review with an empirical case study, this research paper offers an integrative perspective that accounts for both internal firm views (value creation and capture mechanisms) and external ecosystem views (actor coordination and data flows). The result is a conceptualization that explains not only what IoT business model archetypes exist but also how firms transition between them as they pursue more sophisticated value propositions.

The second contribution relates to the conversation on business model sophistication. This study extends the notion by framing it as a multi-faceted concept encompassing the integration of technological capabilities, value creation potential, and multi-actor nature in IoT contexts. While a few studies (e.g., Rupeika-Apoga et al. 2022; Toorajipour 2025) embrace this broader perspective, most earlier conceptualizations (e.g., Muegge and Mezen 2017; Rajagopal 2021), particularly Kesting and Günzel-Jensen (2015), treat sophistication primarily as the realization of secondary value-capturing opportunities beyond the core offering. Our study broadens this view by arguing that sophistication emerges not only from secondary opportunities but also from advanced technological capabilities, complex service-based offerings, and unique customer solutions. The typology developed here shows that business models move from connectivity to servitization and ultimately to data ecosystems. This view suggests a deepening capacity to orchestrate complex value flows rather than merely extracting adjacent value. This progression provides a richer lens for analyzing how firms transition toward more holistic and collaborative models of value creation. In the same vein, much of the prior literature, including Endres et al. (2019) and Cranmer et al. (2022), has treated IoT business model categories as discrete types without theorizing their interrelationships or developmental trajectories. In contrast, the present study employs sophistication as an axis along which business models can evolve. This perspective allows for not only a better understanding of IoT business model archetypes but also an appreciation of how firms dynamically reconfigure value creation and capture mechanisms as their technological maturity and ecosystem roles expand.

The third contribution of this study lies in its intersection with the literature on data ecosystems (e.g., D'Hauwers et al. 2022; Oliveira et al. 2018; Toorajipour et al. 2024), and more specifically, IoT data ecosystems (e.g., Khezr et al. 2022; Krishna et al. 2021; Sohail and Tabet 2025). The findings of this study contribute to the mainstream literature on data ecosystems by reframing the data ecosystem concept as a business model archetype rather than a socio-technical network of actors. Existing studies predominantly conceptualize data ecosystems as complex networks of actors collaborating to manage and exchange data for collective benefit, often emphasizing governance structures, interoperability, and data sharing processes (Aaen et al. 2022; Curry et al. 2021; Oliveira et al. 2018). By identifying "data ecosystem" as a business model archetype within the IoT context, this study introduces a novel perspective: business models themselves can become the organizing logic of ecosystems, serving as focal points around which value-creation and value-capture mechanisms form and evolve. This augments prior work by offering a new perspective on the data ecosystem in the existing literature.

Another critical point is that mainstream data ecosystem research tends to treat these ecosystems as socio-technical systems (e.g., Liva et al. 2023; Šestak and Copot 2023), where value is created through the utilization, sharing, and processing of data, but often overlooks which business model archetypes enable this value creation in the first place. The literature also tends to underemphasize the role of business model archetypes in shaping ecosystem roles and functions. While this study fully aligns with existing research that conceptualizes data ecosystems as sociotechnical networks in which firms utilize data and technological infrastructure to create value (Hrustek et al. 2023; Legenvre et al. 2020; Neff et al. 2024), it also extends this literature by suggesting a new perspective where data ecosystems are understood as a business model archetype. This perspective does not challenge established ecosystem-based interpretations; rather, it complements them by explicitly linking ecosystem configurations to firm-level logics of value creation and value capture (Amit and Zott 2001; Zott and Amit 2010). The unique contribution of this study lies in framing data ecosystems as business model archetypes, thereby providing a novel lens that more clearly connects data ecosystems with the logic and components of business models. In this way, the study reinforces, supports, and extends core ideas discussed in prior work (e.g., D'Hauwers et al. 2022; Toorajipour et al. 2024), while offering a distinct perspective that bridges ecosystem research and business model theory.

By framing data ecosystems as a highly sophisticated business model archetype within a progression-based structure, this study highlights how firms potentially evolve from basic connectivity to multi-actor formations. The present study contributes to IoT-specific data ecosystem research, which remains underdeveloped compared to general data ecosystems conversation. While IoT data ecosystems are mostly discussed from a technical perspective (e.g., Khezr et al. 2022; Krishna et al. 2021; Sohail and Tabet 2025), prior research offers limited insights into the business model aspects of the topic. By positioning data ecosystems as an IoT business model archetype with a progression trajectory, this study bridges the technical focus of IoT data ecosystem research and the business model perspective. It therefore provides a conceptual foundation for analyzing not just the technicalities of IoT data ecosystems but also the business-oriented pathways through which firms can utilize value-creation and value-capture mechanisms.

6.3 Practical contributions

Beyond the direct theoretical contributions, the suggested typology of IoT business models has two major implications for practitioners. First, understanding the diverse nature of IoT-enabled business models in terms of sophistication is critical to aligning strategic goals, particularly when the focal firm is focused on its technological capabilities and potential market opportunities. Companies can integrate IoT technologies into their offerings for various purposes and in different forms. However, without a clear understanding of how these technologies can support their business goals and strategies, such investments and efforts may be less effective or even futile. The second implication is that this typology enables companies to align their business models with the needs of their target customers, aiming at optimal customer value. This alignment is critical for maximizing the impact of technology investments and ensuring that customers do not receive offerings that are either technologically underdeveloped or overdeveloped, thereby avoiding unnecessary expenditure on suboptimal solutions. This framework not only helps to identify suitable business models based on current capabilities but also guides future development and competitive positioning in the evolving IoT landscape. Companies can leverage this typology to design and implement IoT strategies that maximize value creation and capture. For instance, transitioning from connectivity to servitization can enhance customer engagement and generate recurring revenue streams through subscription-based services. Embracing data ecosystems can unlock new markets and foster innovation through collaborative partnerships. These insights are crucial for firms aiming to exploit the potential of IoT technologies and to achieve a competitive edge.

While the identified IoT business model archetypes and the progression framework offer a coherent understanding of data-driven value creation and capture, their applicability and progression are likely to vary across firm types and industry contexts. Large incumbent firms operating in capital-intensive industries, such as manufacturing, infrastructure, and industrial services, appear to be better positioned to utilize servitization and data ecosystem models due to their installed base, longer-term relationships, and access to greater resources. Firms in consumer-oriented or less asset-heavy industries may face greater constraints in managing or orchestrating ecosystem-level models, given that such configurations require significant investments in data governance, interoperability, and partner coordination. Smaller firms, on the other hand, while potentially more agile in adopting IoT-enabled connectivity solutions, may lack the scale or the foundations needed to sustain advanced ecosystem roles. As a result, they are more likely to position themselves as participants rather than orchestrators of an ecosystem. These observations suggest that progression toward higher levels of business model sophistication is neither linear nor universally attainable, but rather contingent on a company's industry positioning, the characteristics of its offerings, and organizational capabilities.

From a managerial and policy perspective, the findings provide actionable recommendations. Managers and decision makers should systematically assess their data and technology readiness, including the quality, interoperability, and governance of IoT technologies and IoT-driven data, before pursuing more advanced business model configurations. Investments in IoT infrastructure, data analytics capabilities, system architectures, and cybersecurity are critical prerequisites for moving beyond basic connectivity toward servitization and ecosystem-based models. Moreover, firms seeking to participate in data ecosystems should proactively develop data-sharing strategies and regulations that address data ownership, access rights, and governance among partners. For policymakers, these insights highlight the importance of supporting standardization efforts, interoperable digital infrastructures, and regulatory frameworks that facilitate data flow across organizational boundaries. Policies that lower barriers to collaboration can also help firms—particularly smaller actors—to engage more effectively in IoT-enabled networks and ecosystems.

While the framework has been developed primarily based on established organizations, its analytical logic is also applicable to SMEs and digital-native firms. SMEs may adopt connectivity or servitization models in more focused or niche configurations, leveraging agility and specialization. However, their ability to orchestrate full-fledged data ecosystems may be constrained by limited resources, user base, or bargaining power, often positioning them as participants rather than orchestrators. Digital-native firms, in contrast, may more readily design ecosystem-oriented models from inception, as their architecture and governance mechanisms are typically built around data-centric and platform-based logics. Thus, while the framework is conceptually transferable across firm types, the pathways, pace, and strategic positioning within each archetype are likely to vary depending on organizational capabilities, market positioning, and technological maturity.

6.4 Limitations and future research

While our study provides a novel framework for understanding IoT business model archetypes and their sophistication, it is not without limitations. This study suggests some avenues for future research and the areas that need further exploration. Our study utilizes a systematic literature review and a multiple case study design, a robust and well-established approach, with data from 14 case companies and an inductive analysis. However, the scope of data collection could be expanded. Future studies, for instance, could employ surveys with a larger number of respondents to gather data from more companies and extend our understanding of IoT business models through more deductive approaches. The current study prioritizes depth and analytical insight over statistical generalizability, given its exploratory nature. While this approach is well-suited to theory building and development, the findings may reflect dynamics specific to certain contexts or technologies. Future research could address these limitations by quantitatively validating the proposed typology and progression framework employing large-scale surveys or using archival data. Such studies enable the statistical testing of relationships between IoT data utilization and business model sophistication. In the same vein, longitudinal studies tracking the evolution of IoT business models over time would be valuable in understanding the dynamic nature of sustainable growth and market adaptation.

Another limitation of this study lies in its economic view of value. Here, value—particularly in terms of value capture—refers to economic gains. This perspective reflects a more traditional approach in business model research, grounded primarily in economic value creation and capture. Economic and financial metrics are especially tangible, measurable, and accessible to companies when assessing their strategies and market positions. Additionally, economic value is a core element of business model theory, which traditionally prioritizes profitability and financial sustainability as central to a model's success. Such a viewpoint may not fully account for the broader impact that IoT-enabled solutions have on environmental and societal well-being. For example, IoT technologies can drive substantial environmental benefits, such as reducing carbon footprints through smart grids or optimizing resource usage in industrial settings. Similarly, societal benefits, including enhanced public safety or improved quality of life through smart city initiatives, represent significant non-financial value created by IoT business models. This broader impact is essential to consider, particularly as contemporary business practices increasingly emphasize sustainability, social responsibility, and long-term societal value.

While non-financial values are undoubtedly important, especially in the context of IoT, capturing these broader forms of value comprehensively requires a significantly expanded scope beyond the reach of a single study. Addressing every potential value dimension in one typology could dilute the clarity and focus necessary to create actionable insights for practitioners. Therefore, we suggest that future research explore the non-financial dimensions of value in IoT business models to provide a more holistic understanding of their impact. Studies could examine how IoT can support sustainability initiatives, reduce environmental footprints, or promote social well-being, providing a framework that aligns with the growing importance of sustainable development goals (SDGs) in business practice. Additionally, research could investigate metrics and models for measuring these non-financial values, helping companies balance economic gains with their environmental and societal responsibilities. Here, we suggest two propositions for future research. These may take the form of testable hypotheses in quantitative studies or serve as guiding ideas for qualitative research:

Proposition I *Highly sophisticated business models can directly enhance a firm's capacity to capture higher economic and non-economic value.*

Proposition II *Highly sophisticated business models may entail higher technological costs in the short to mid term; however, these costs can be justified by higher returns on investment in the long term.*

Moreover, future research could examine the specific challenges and barriers associated with each business model archetype and provide deeper insights into the implementation of these business models and the scalability of their IoT-enabled offerings. Finally, extending this framework to other domains, such as smart cities, agriculture, and healthcare, could validate and refine the typology across different contexts.

6.5 Concluding remarks

This study has examined IoT business models by developing a typology and progression framework grounded in a systematic literature review and evidence from a multiple case study. The analysis identified three archetypes: connectivity, servitization, and data ecosystems. They represent increasing levels of business model sophistication and highlight the progression from basic device interconnectivity toward collaborative, data ecosystems. By conceptualizing this evolution, this study provides a dynamic perspective on how IoT capabilities transform value creation and capture mechanisms over time. Theoretically, this work makes three contributions. First, it advances the IoT business model literature by positioning the identified archetypes within a progression framework and by bridging static classifications and evolutionary perspectives. Second, it extends the notion of business model sophistication by integrating technological aspects, service orientation, and multi-actor views into a single construct that explains how firms transition toward more advanced value propositions. Third, it augments the data ecosystem literature by framing data ecosystems as a business model archetype, demonstrating how they emerge from earlier IoT configurations, and marrying data ecosystem theory with business model research. Practically, the framework provides firms with a strategic lens to assess their current business model position and plan pathways toward greater sophistication. Moreover, understanding the transition to data ecosystems can guide firms in orchestrating multi-actor collaborations and leveraging data as a core strategic asset. Future research could build on this work by broadening its scope through larger-scale, quantitative approaches, such as surveys, and by focusing on non-financial dimensions of value in IoT business models. Such studies would deepen understanding of IoT business models, their evolution, and their role in broader digital transformation agendas.

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Declarations

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