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Harnessing Artificial Intelligence for Value Creation and Capture: Strategic Implications of the EU Artificial Intelligence Act within Business Model Theory

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ABSTRACT

This article aims to offer a novel answer to the following question: How can firms use artificial intelligence (AI) technology to create and capture value, specifically through predictive machine learning? This article analyses ten papers by the same author on the themes of value creation through AI. These papers include conceptual research, empirical cases, and case-based theory building. These exploratory cases explore the management of AI capabilities in business models using a variety of methodologies, including systematic reviews, statistical regression, and qualitative comparative analysis (QCA). To enhance the theoretical and practical insights arising from this research, the article adds a regulatory dimension to the analysis by discussing the European Union (EU) Artificial Intelligence Act. The results show that AI can create perceived user value and enable the realization of data network effects. When applied within a firm's business model architecture, AI can activate one or more of the four available business model themes (novelty, efficiency, complementarity, and lock-in) that account for value creation and capture. This study contributes to understanding how a firm can use this new technology to create value. The findings suggest that integrating AI into business models is essential for delivering user value and fostering data network effects. Managers play a crucial role in coordinating AI deployment across all business activities. The findings reveal that firms must not only activate the appropriate business model themes (e.g., novelty, efficiency, and lock-in) but also ensure compliance with evolving regulatory standards to secure sustainable competitive advantage. This study adopts a multitheoretical approach based on business model theory and the theory of data network effects. However, authors of further studies should consider using large samples and testing the findings in different contexts to enhance generalizability.

1. Introduction

Despite remarkable technological progress in artificial intelligence (AI), its impact on economies and firms has been relatively modest (Brynjolfsson & Mitchell, 2017; Shollo et al., 2022). AI appears in a variety of business areas, including business models and corporate offerings, business processes, and work itself (Ransbotham et al., 2017; Tarafdar et al., 2019; Wiener et al., 2020). Although some of the world's most highly valued firms have adopted AI as a strategic enabler (Parker et al., 2016), integrating AI into firm operations presents challenges and obstacles (Duan et al., 2019). To realize the potential value of AI, firms must understand how to overcome these challenges, have the right strategy, and create and capture value as an outcome of AI technologies. In this research, a firm is conceptualized as an economic institution that performs transactions internally only if the cost of doing so is lower than performing transactions through a market (Roberts, 2007).

Recent research has focused on AI adoption from a technological perspective rather than identifying the organizational challenges associated with its implementation (Alsheibani et al., 2020). Mikalef and Gupta (2021) noted research gaps and analyzed the effective use of AI technologies, emphasizing the need for a comprehensive understanding of AI adoption and value generation in firms due to its complex and varied implications. The current research adds a novel dimension to the analysis by considering the implications of the European Union (EU) Artificial Intelligence Act (AIA) (Smuha, 2024). This legal framework governs the design, deployment, and oversight of AI systems in high-risk contexts. The aim of this study is to answer the following research question: How can firms use AI to create and capture value in a regulatory environment shaped by the AIA? Firms considering investing in AI technology can use the answer provided to this question to guide their decision-making in the EU.

In response to this research question, this article presents a research model that integrates the theory of data network effects (Gregory et al., 2021) with business model theory (Amit & Zott, 2001; Teece, 2010) and business model themes (Leppänen et al., 2023; Zott & Amit, 2008). From a practical perspective, this article describes ten research papers whose results comprehensively answer the research question. Regarding the scope of this research, only firms in liberal or democratic markets were considered. Thus, government organizations, nongovernmental organizations (NGOs), and other types of markets were excluded. Furthermore, emphasis was placed on ***discriminative AI***, as opposed to ***generative AI***, such as ChatGPT. The main focus of AI was machine learning (ML). Shaw et al. (2019) noted that ML, which is a subset of AI, profoundly affects all industries. ML uses computer programs to process data, derive meaningful insights, make forecasts, and recommend actions through learning, reasoning, and data-driven decision-making. Given that AI and ML are subfields of information technology (IT), understanding their value requires anchoring them within the broader IT literature. This idea lays the foundations for the theoretical framework presented in the next section.

The results of these ten research papers could mark a breakthrough in the theory of data network effects on the use of ML for value creation and capture. The findings highlight the role of institutional rules in business model innovation and the way in which firms leverage ML to create and capture value. To address the identified research gap, the article is structured as follows. Section 2 develops the theoretical framework, integrating business model theory with the theory of data network effects. Section 3 outlines the methodological approach based on ten academic studies. Section 4 presents the main findings of these studies. Section 5 discusses the theoretical and managerial implications. Section 6 concludes with reflections on the limitations of the research and directions for future inquiry.

2. Theoretical Framework

This section emphasizes the need for studies to identify the value presented by ML technologies and their capabilities. The academic literature on IT's impact on business performance is often treated as a black box. The review explores how business model theory explains IT-based value creation and identifies the unique capabilities of ML technology.

2.1. The Value of Using Information Technology

The impact of IT on organizational performance is a core research stream. IT can increase productivity, improve profitability, reduce costs, create competitive advantage, reduce inventory, and boost other metrics (Devaraj & Kohli, 2003; Hitt & Brynjolfsson, 1996; Melville et al., 2004). IT hardware and software tools generate value when integrated into a value-creation process with other IT and organizational factors (Melville et al., 2004). IT value is influenced by various factors, including the IT type, management practices, organizational structure, and a competitive and macroeconomic environment (Brynjolfsson et al., 2002; Dewan & Kraemer, 2000). Crucially, IT-based value creation takes time. The effect of IT adoption, implementation, and acceptance can span several years, as Santhanam and Hartono (2003) explained. The text discusses how IT generates value through ML technologies.

2.2. Artificial Intelligence in Firms

AI can mimic human cognitive functions such as problem-solving and learning (Lee et al., 2019). This article defines AI as the applied discipline of enabling systems to identify, interpret, make inferences, and learn from data to achieve predefined organizational and social goals (Enholm et al., 2022).

Firms implementing AI applications are expected to achieve value gains such as increased revenue, reduced costs, and improved business efficiency (Alsheibani et al., 2020; Enholm et al., 2022). ML technologies enable firms to use big data, data storage, and computer speed to make predictions, gain insights into customer behavior, and personalize offerings for a competitive advantage (Agrawal et al., 2019). ML algorithms are valuable for enhancing tasks that seek to maximize or automate processes (Arel et al., 2010; Shaw et al., 2019). Irrespective of the business and its context, when there is access to sufficiently large sets of data, ML can enhance operational outcomes more effectively than other technologies (Agrawal et al., 2019). The ability of ML to learn from data by mining for patterns and making predictions reduces the dimensions of relevant information, lowers cognitive costs, and leads to faster, higher-quality decisions, thereby increasing digital information performance (Brynjolfsson et al., 2021).

Many firms invest in AI or ML technologies for competitive advantage (Fountaine et al., 2019). Although firms allocate time, effort, and resources to AI adoption, its anticipated benefits may not materialize (Makarius et al., 2020). Brynjolfsson and Mitchell (2017) argued that the AI productivity paradox can be attributed to implementation delays and the need for organizational restructuring.

There is a scarcity of empirical research on the decision-making processes of organizations concerning the degree of augmentation or automation (Coombs et al., 2020), the specific value they aim to generate with AI (Lyytinen et al., 2020), and the strategies employed to extract value from AI (Berente et al., 2021; Günther et al., 2017). In response to this research gap, the present article heeds calls from information systems researchers (Coombs et al., 2020; Rai et al., 2019) and management scholars (Raisch & Krakowski, 2021; von Krogh, 2018) to explore how firms pursue their value objectives through AI applications (Shollo et al., 2022). To contextualize the findings, the theoretical foundations are first described.

2.3. Business Model Theory

A growing body of research is now dedicated to exploring how business models can elucidate firms' endeavors to create and capture value (Chesbrough & Rosenbloom, 2002; Leppänen et al., 2023; Snihur et al., 2021; Teece, 2010; Tidhar & Eisenhardt, 2020; Zott & Amit, 2010). The business model articulates the business logic employed by a firm, delineating how it creates and delivers value to customers while also outlining the revenue, cost, and profit architecture (Teece, 2010).

The business model is defined as the content, structure, and governance of transactions designed to create value by exploiting business opportunities (Amit & Zott, 2001; Teece, 2010). Firms seek to maximize their performance, and evidence shows that successful firms employ one or more business model themes, namely novelty, efficiency, complementarity, and lock-in (Amit & Zott, 2001; Leppänen et al., 2023). The novelty business model theme means using digital technology to conduct business differently from other firms in the target marketplace (Comberg & Velamuri, 2017). The efficiency business model theme means using digital technology to conduct business by deploying fewer resources than competitors (Ritala et al., 2014). The complementarity business model theme involves bundling offerings, activities, and resources to create synergies. The lock-in business model theme creates demotivating effects for actors to switch to another firm's business model.

The application of these themes creates a business model configuration aligned with one or more of the four structures that can be used for value creation and capture (Amit & Zott, 2001; Kulins et al., 2016; Leppänen et al., 2023; Zott & Amit, 2008). Empirically, firms that pursue a particular business model theme, or a combination of them, can outperform their competitors (Kulins et al., 2016; Leppänen et al., 2023; Zott & Amit, 2007).

AI's transformative and disruptive nature underscores the necessity for business models and firms to undergo a major shift to harness AI's full potential (Chesbrough, 2007; Lee et al., 2019). This imperative arises because AI technology fundamentally diverges from other IT, presenting novel organizational opportunities and challenges. First, AI can substitute, complement, or restrict human involvement in various tasks (Murray et al., 2021). Second, AI use blurs the line between human and machine capabilities (Schuetz & Venkatesh, 2020). Third, the data-driven learning inherent in ML introduces an experimental element (Choudhury et al., 2018), potentially leading to unforeseen outcomes (Benbya et al., 2020).

Given the critical distinctions between AI technologies and other digital technologies (Benbya et al., 2020), coupled with the transformative impact of AI-enabled business models (Burström et al., 2021), there is a pressing need for further investigation and theoretical development in the realm of AI-driven business models. Business model theory emphasizes the role of IT in creating and capturing value for firms. However, it overlooks the distinctive capabilities of different technologies.

2.4. Theoretical Framework of Value Creation and Capture through Artificial Intelligence

The research on creating and capturing value using digital technologies tends to treat digital technology as a homogeneous concept (Orlikowski & Iacono, 2001). Different digital technologies have unique characteristics with varying impacts on firm performance (Berg et al., 2023; Gregory et al., 2021; Kemp, 2023). Neglecting this feature of digital technologies is also an issue in business model studies of digital technology use (Amit & Zott, 2001; Leppänen et al., 2023).

This research focuses on how to create and capture value using AI technologies. Recent theoretical developments have addressed this disregard for the unique characteristics of different digital technologies in the theory of data network effects (Gregory et al., 2021).

The recent theory of situated AI for competitive advantage focuses on how firms can use AI to establish competitive advantage (Kemp, 2023). A firm's competitive advantage is achieved through specific, cost-effective AI-enabled capabilities that fit the environment. AI theory (Kemp, 2023) identifies three critical activities for achieving competitive advantage using AI: grounding, bounding, and recasting. However, it mainly emphasizes competitive advantage over value creation and capture. Competitive advantage may or may not lead to value creation (Grahovac & Miller, 2009; Hossain et al., 2021) because many other factors are involved in achieving competitive advantage, which may be beyond the firm's agency.

The theory of data network effects (Gregory et al., 2021) explains how AI technologies provide user value through speed and predictive accuracy, influenced by data ownership, legitimacy, and user-centered design. Data ownership accounts for the quality and quantity of data needed for a specific service. Legitimacy accounts for personal data use and prediction explainability. User-centric design accounts for the user's performance expectancy and effort expectancy. That is, if a user expects high performance with little effort, then the user is more likely to use that service and generate new data to feed data network effects. Although this theory has received preliminary empirical support (Costa-Climent et al., 2023; Haftor & Climent, 2021), it focuses on individual perceptions of value. The theory of data network effects does not address how AI technologies create and capture value. A second limitation of the theory of data network effects is its static view of data network activation using ML, failing to consider the dynamic processes involved in implementing ML technologies and maintaining data network effects. This research presents ten examples (research papers) of how business model theory and the theory of data network effects have been used to design and conduct empirical studies to identify the factors involved in creating and capturing value through firms' AI use.

2.5. The Artificial Intelligence Act as a Regulatory Enabler of Business Model Innovation

The EU AIA (Madiega, 2021) introduces a risk-based legal framework that shapes how firms deploy AI technologies. By requiring safeguards such as transparency, human oversight, and risk assessments, the AIA affects the conditions under which firms can activate business model themes such as novelty, efficiency, and lock-in. Rather than acting solely as a constraint, the AIA (Madiega, 2021) can enable value creation by enhancing trust, legitimizing data use, and supporting sustainable data network effects. Thus, it serves as both a regulatory boundary and a strategic lever for AI-driven business model innovation.

3. Methodological Approach

This article analyses ten academic papers on the factors involved in creating and capturing value through AI. They are presented according to the studies' logical order rather than chronological order, following Eisenhardt's case-based theory-building research strategy (Eisenhardt & Graebner, 2007). The article adds a regulatory dimension to the analysis by discussing the EU AIA (Madiega, 2021) to enhance the theoretical and practical insights of the research.

Existing theories that provide partial answers to the research question were adopted. The advantage of such an approach is that it builds on existing research that provides relevant insights, thereby shortening the process of answering the research question. Consequently, an abductive mode of enquiry was followed (Tavory & Timmermans, 2014). The existing theories adopted for this research were compared and contrasted with empirical experiences.

The adopted theories can confirm some of these experiences. In contrast, others might need theory modification and development (Behfar & Okhuysen, 2018). Abductive reasoning enabled discovery of new features and relationships while linking the findings to an existing body of theory (Tavory & Timmermans, 2014).

This set of studies answers the research question in line with evolutionary epistemology (Bateson, 2000). One strength of this research is the presentation of empirical studies of different related and unrelated firms, thereby providing a range of perspectives. The research used various data collection and analysis methods, including observations, interviews, documents, surveys, data coding, statistical analysis, and qualitative comparative analysis (QCA). This methodological diversity ensured robustness to bias and greater generalizability of findings.

4. Results

The following section analyses ten papers, which are labelled as Papers 1–10 for ease of reference. The analysis of these ten papers gives an overview of firms' value creation and capture using ML. A summary of each article and its contributions is provided in Table 1.

Table 1. *Summary of papers and their main contributions.*

Paper no.	Research question	Received theoretical foundations	Methodology	Findings	Citation
1	What are the merits of the recently proposed theory of data network effects?	Data network effects	Conceptual scrutiny	The theory of data network effects offers a novel explanation of how ML can give rise to perceived user value. It accounts for ML's unique learning capability. However, the theory has several limitations that deserve further research.	Costa-Climent (2023)
2	How can a firm create and capture economic value using AI?	None	Systematic literature review	The review identifies a knowledge gap regarding empirical research that provides answers to the question at hand. Studies tend to black-box ML technology by treating it as a monolith and disregarding its unique learning capabilities.	Costa-Climent (2022)
3	How effectively can business model theory account for changes in the focal firm's industry?	Application of evolutionary economics theory to a business model	Conceptual scrutiny and development	A key limitation of business model theory is identified, namely its assumption of a static firm context. A theory of the evolutionary transformation of the business model in terms of a firm's sources of value creation is proposed. These sources must co-evolve in synchrony with the firm's context.	Climent & Haftor (2021a)
4	How effectively can business model theory predict future uses of digital technology by a firm?	Business model theory, specifically the notion of business model themes and their activation through the use of digital technology, and the recently proposed theory of evolutionary activation of business model themes	Formulation of predictions derived from theoretical base for firms' technology uses; longitudinal investigation of an industrial niche of haemophilia products; qualitative and quantitative data to identify evolving uses of technology by firms	The unfolding uses of technology largely confirmed predictions. In an exploratory sense, the results show potential for ML-powered realization of data network effects.	Climent & Haftor (2021b)
5	What mechanisms can be used by industrial organizations to provide offerings that reduce their negative impact on the natural environment?	Multiple theories to examine strategic pathways for environmental sustainability in firms	Longitudinal study of an international heavy truck manufacturing company (TruckCo) using qualitative analysis in ATLAS software	The firm's underlying mechanisms, revealed by different theoretical lenses, are interrelated. Its dynamic activities led to the development of new operational capabilities and strategic networks with extensive supply chains. The company's innovative use of digital technologies reduced transaction costs and enabled direct and data-driven network effects. This situation allowed for the introduction of a new product-service system, EcoDrive, as a niche differentiation strategy, representing a Schumpeterian innovation. Successfully launching EcoDrive required the company to align competing institutional logic as an institutional entrepreneur.	Haftor & Climent (2021)
6	Can the concept of the business model be extended to account for data network effects?	Business model theory; theory of data network effects	Qualitative longitudinal case study of an industrial firm	A business model designed to realize data network effects can activate value creation themes. Specifically, data network effects can improve efficiency, novelty, lock-in, and complementarity.	Haftor et al. (2021)
7	What pathways can small and medium-sized enterprises (SMEs) follow to enter a market with entry barriers that arise from incumbents' data network effects?	Theory of direct and indirect network effects; theory of data network effects; industrial organization theory; institutional theory; market entry theory	Exploratory longitudinal case study of the evolutionary path of a start-up	A start-up can gain legitimacy by accessing and using incumbents' unique data while identifying latent users of services based on that data, who hold the power to legitimize the use of the data.	Haftor et al. (2023)
8	What factors condition a start-up's value creation and capture using ML technology?	Business model theory; theory of data network effects; evolutionary economics	Statistical regression analysis based on Twitter data	The efficiency business model theme has a big impact on company funding, while the novelty business model theme is very prominent. Business model themes and performance expectations affect data network effects. Network size does not have a significant role. Efficiency is prioritized before the first round of funding.	Costa-Climent et al. (2023)
9	How do business model themes and the moderators of data network effects interact to allow AI-based start-ups to create and capture value?	Business model theory; theory of data network effects; evolutionary economics	Fuzzy-set qualitative comparative analysis (fsQCA)	Early funding is positively associated with value creation and capture for AI start-ups. Key elements include efficiency, novelty, and performance expectations.	Costa-Climent et al. (2023)
10	How can firms use AI technology to create and capture economic value?	Business model theory; theory of data network effects; evolutionary economics	Comparative study based on a unique natural experiment with two similar industrial firms in head-to-head competition that adopted similar uses of AI	The study shows that one firm successfully used AI, achieved data network effects, and activated several business model themes. The other firm failed in its use of AI, its realization of data network effects, and the activation of business model themes. These differences translate into proportional differences in market share performance.	

Source: Authors' own creation.

Part of this research program involved reviewing the business value of using ML-based AI in information systems. This review tested the literature's ability to offer a differentiated explanation of ML and its ability to create and capture value. Research in this area is scarce, with a predominance of research on the value of using ML in manufacturing and computing and virtually no studies of value capture through ML (Paper 1). Business model theory (Amit & Zott, 2001) posits four related value drivers (novelty, efficiency, complementarity, and lock-in) that explain how a firm's use of IT can create value (Amit & Zott, 2001; Zott & Amit, 2007; 2008). It provides a promising theoretical framework to address this research gap.

Business model theory has a limitation due to its mostly static view of value creation and capture. To solve this limitation, evolutionary economics theory was used in tandem to analyze business model value creation and capture (Papers 3 and 4). Thus, a dynamic notion of value creation and capture through a firm's business model was adopted. This activation pattern reveals how different business model theory value creation themes are successively activated from novelty and/or efficiency to complementarity and/or lock-in (Paper 3). Five predictions were deduced from business model theory and the co-evolutionary pattern of activation of the business model themes (Papers 3 and 4), showing that business model theory can predict firms' value creation and capture from adopting IT in a niche sector (Papers 3 and 4).

The findings advance the theoretical conception of the predictive ability of business model theory while illustrating how institutional rules govern firms' business models (Papers 4 and 6) and identifying possible gaps in predicting value creation and capture using ML-based AI technology (Papers 4 and 6). Business model theory conceptualizes firms' use of AI solely concerning the ability to create direct and indirect network effects (lock-in). Thus, while business model theory constitutes an excellent framework for answering the research question, it ignores the uniqueness of each form of IT and hence the unique learning capabilities of ML-based AI.

Under this multitheoretical approach, the theoretical lenses underpinning business management theory were used to explain value creation and capture by a specific firm that innovated its business management approach with the help of new uses of transport technology (Paper 5). The research reveals a sequence of activities for business management innovation enabled by transport technology. This study supports the proposed dynamic view of the business model (Papers 2 and 3).

When the theory of data network effects is introduced (Paper 5), Paper 4 should be reinterpreted. The theory of data network effects helps articulate how value is created for users of the ML-enabled service. The study shows that the theory of data network effects can be linked to business model theory. Business model theory articulates four drivers of firm value. The theory of data network effects specifies how user value is created, while business model theory explains what value is created and captured. Attempts were made to integrate business model theory with the theory of data network effects (Papers 6, 7, 8, 9, and 10). A more holistic view of how firms can leverage ML to generate value across multiple dimensions, including novelty, efficiency, and lock-in, was adopted. A business model created to achieve data network effects helps activate three business model themes of value creation and capture. Through novelty, the focal company is the pioneer in its market segment. Through efficiency, resource use is reduced, thanks to learning and improvement. Through lock-in, improvements provide superior offerings (Papers 3, 4, and 6).

When a start-up establishes user services and activates data network effects, users are reluctant to switch to alternative providers owing to the superior service enabled by large, unique data sets. This situation creates user lock-in associated with the pioneer's large sets of user data, posing barriers for new entrants, particularly small and medium-sized enterprises (SMEs). This study advances the perspective on ML-driven business models and updates the theory of data network effects through empirical testing of user perceptions.

Paper 8 provides regression-based empirical analysis of the relationship between specific value creation and capture factors according to business model theory and the theory of data network effects. The article analyses the relationships between the value creation and capture factors proposed by these two theories, such as efficiency, novelty, and performance expectancy. It also discusses the importance of taking a co-evolutionary perspective on value creation and capture using ML. It offers empirical evidence for theoretical premises of the theory of data network effects, such as the moderating role of performance expectancy and effort expectancy in value creation using ML. These two theories reveal that ML successfully combines value creation and capture factors.

The next study used fuzzy-set qualitative comparative analysis (fsQCA) (Paper 9). It identified combinations of business model features (namely novelty, efficiency, and performance expectancy) that are linked to early funding success. The analysis emphasizes the importance of designing for value capture early in the AI adoption process, especially when leveraging novelty-based business models. The study used a configurational approach linked to performance. The overall configuration of multiple business model features can be beneficial. Efficiency is essential for attracting funding. Novelty is relevant for value creation. It underlines the need for design mechanisms focused on value capture to make the most of novelty.

Finally, Paper 10 presents the hypothesis that a business model in which an actor uses an AI-enabled service that triggers positive data network effects activates one or more business model themes, thereby increasing business performance. The study supports the J-curve model for AI value creation and identifies failure factors in AI use. Low investment in technical infrastructure and limited user training contribute to failure in some AI use cases. The paper also highlights the time lag before the value generated by AI is reflected in meaningful change.

The analysis of the ten studies is complemented by inclusion of the EU AIA as a contextual variable influencing firms' capacity to realize value from AI. The AIA introduces binding requirements, particularly in high-risk systems, that affect firms' strategic and operational decisions. Empirically, firms that succeed in creating and capturing value through AI do so by activating business model themes and aligning with regulatory principles such as transparency, data governance, and user trust. This alignment strengthens data network effects and enhances the perceived legitimacy of AI-enabled services.

These studies form an overall framework that answers the following general research question: How can firms use AI technology to create and capture value? The conclusion is that a firm's ability to create and capture value using AI depends on the firm's ability to activate specific business model themes that enable economic value creation. Successful use of ML technology involves a dynamic link between the business model, data network effects, institutional rules, and user-based value creation strategies using AI or ML.

5. Discussion

The review of the mainstream literature on IT and value creation and capture shows isolated islands of productivity and profit value drivers related to innovation and/or efficiency (Chae et al., 2014; Hitt & Brynjolfsson, 1996; Kohli & Grover, 2008; Porter, 2001). Emerging theory on data network effects (Gregory et al., 2021) sheds light on this gap but has limitations such as the need to consider the capture of value created using ML (Costa-Climent, 2023).

Much of the research on value creation and capture through digital technologies treats digital technology as a homogeneous concept (Orlikowski & Iacono, 2001).

However, different digital technologies have unique characteristics that affect firm performance (Berg et al., 2023; Gregory et al., 2021; Kemp, 2023). Neglecting this feature is also a problem in business model studies of digital technology use (Amit & Zott, 2001; Leppänen et al., 2023). This neglect is compounded in the case of AI owing to its unique learning and predictive capabilities (Haftor et al., 2024). Exploration of the dimensions of AI in business reveals a range of theoretical perspectives (Enholm et al., 2022). Several studies have used firm-level theories, such as the enterprise theory framework and the resource-based view of the firm (Demlehner & Laumer, 2020), to examine aspects of effective adoption and implementation of AI applications from an organizational perspective (Brynjolfsson & Mitchell, 2017; Tarafdar et al., 2019). Other research streams address AI development processes and the knowledge-intensive practices associated with their evolution (Quinio et al., 2017). Some studies have focused on the individual as the unit of analysis under dual process theory, studying human–AI interactions to optimize decision-making (Castillo et al., 2021).

Despite these advances in research on the use of AI in business, the in-depth literature review during this research program revealed a lack of specific research on value creation and capture using AI technologies in business, especially in information systems (Costa-Climent, 2022; 2023). This initial gap highlights the relevance of exploring how firms can harness the potential of AI for value creation and capture.

The theory of data network effects offers a promising explanation of the unique characteristics of ML-based AI technologies that can create value when used (Gregory et al., 2021). It asserts that AI's prediction speed and accuracy generate perceived value for users. In general, research on the value of IT consistently reports a positive relationship between IT and some aspects of firm value (Kohli & Grover, 2008). However, the theory of data network effects considers the unique ability of ML-based AI technology to create value.

The theory of data network effects specifies the factors and their relationships that jointly co-condition success in a virtuous loop (Gregory et al., 2021). However, this novelty means that the merits of the suggested theory of data network effects need to be assessed (Costa-Climent, 2023). Following a review of the theory of data network effects, a critical evaluation (Costa-Climent, 2023) identified some basic assumptions about them and their potential strengths and limitations. While the theory of data network effects explicitly considers the learning capability of AI technologies for value creation, it needs to consider how to capture the value created through AI in a differentiated way. As a starting point for the current research program, a dynamic and coevolutionary perspective on the activation of data network effects was adopted (Papers 1, 6, 7, and 8). Finally, considering multi-stakeholder user perspectives is crucial in the context of data network effects (Papers 1, 7, and 8).

The business model concept can shed light on these limitations (Papers 1, 3, 4, and 5). Business model theory (Amit & Zott, 2001; Teece, 2010) can explain value creation and capture by IT-using firms by considering the different parts of a business model and the activation of one or more of the value creation and capture themes of novelty, efficiency, complementarity, and lock-in (Amit & Zott, 2001). However, business model theory has a crucial limitation regarding its predominantly static view of value creation and capture (Papers 3 and 4). To solve this limitation, evolutionary economics theory offers a way to analyze a business model's value creation and capture (Papers 3 and 4). A dynamic notion of a business model's value creation and capture can thus be established (Papers 3, 4, 7, and 8), and a development pattern can be identified. This activation pattern reflects how different value creation factors from business model theory are successively activated. First, through novelty and efficiency, a firm can differentiate and access a niche. However, competitors can quickly imitate the firm and attract customers. The original firm must activate complementarity to keep its current customers and attract new ones. If successful, competing firms may imitate it (Lieberman & Asaba, 2006). Successfully activating complementarity will prevent existing customers from migrating to competitors and build a barrier to entry. The focal firm then has two measures to protect its superior performance. The first is to activate lock-in effects further, and the second is to introduce another novelty, thus reinitiating this cycle of theme activation (Balboni et al., 2019) (Papers 3 and 4).

The analysis reveals that the AIA imposes regulatory compliance obligations and influences firms' ability to develop sustainable competitive advantage through AI. By mandating principles such as transparency, human oversight, and data governance, the AIA shapes the institutional context within which firms activate business model themes. Strategic alignment with the AIA can enhance trust, reduce perceived risk, and legitimize data practices. These factors amplify data network effects and contribute to firm-level differentiation. Accordingly, regulatory conformity is integral to competitive positioning, supporting AI's role in long-term value creation and capture (Climent et al., 2024).

In short, a firm's competitive advantage, and thus its sustained economic performance, is conditioned by its evolutionary activation of business model themes as sources of value creation and capture. Therefore, the firm's business model architecture must operate with AI, achieving data network effects that activate the lock-in business model theme (Papers 9 and 10). A firm will thus discourage customers, suppliers, and other actors from migrating from its business model to competitors. Meanwhile, the focal firm generates a unique database that allows it to operate with AI and produce unique services. Doing so will raise the barriers to entry for new competitors while attracting existing actors and new customers.

5.1. Contribution to Theory

This research contributes to the current theoretical understanding in several ways. First, it clearly defines the concept of business models, which are often vaguely delineated (Osterwalder et al., 2005). This study differentiates between firm performance, the activated business model themes influencing performance, and the underlying business model architecture enabling theme activation. This approach underscores the importance of distinguishing these elements to understand AI's role in value creation and capture. A second theoretical advancement is the identification of AI's role within the business model architecture. AI is conceptualized as an active participant in this architecture, influencing internal and external interactions and thus contributing to the manifestation of data network effects within the business model (Amit & Zott, 2001; Snihur & Eisenhardt, 2022). This perspective ensures that AI use in business models is strategically positioned to activate themes and achieve economies of scale on both supply and demand sides (Massa et al., 2017; Zott et al., 2011). The study also acknowledges the need for dynamic adaptation in business models and AI strategies to maintain contextual relevance over time (Leppänen et al., 2023).

5.2. Managerial Implications

This article explains how AI can be used to create and capture value, mainly through ML technologies. Based on ten papers, this article explains that investing in AI technology is insufficient to create economic value for businesses. The key challenge for firms is to use AI to create and capture value effectively. Managers must ensure that AI technology is deployed in such a way as to provide high value to users and to result in data network effects. Accordingly, managers should focus on activities that directly involve the use of AI (e.g., the service activity of technicians) while addressing business model activities that are less directly related to AI (e.g., marketing and sales). Senior executives must do more than advocate the introduction of AI technology.

A coordinated commitment from managers across the business model is essential for successful AI integration.

AI should be integrated into business models that foster data network effects and theme activation to gain strategic benefits. Revaluating and adjusting AI integration within business models is crucial for sustained success. Similarly, the emphasis on institutional and multi-stakeholder dynamics can be helpful in the design of a business model. Practitioners can use this knowledge to identify and overcome potential barriers to using AI and ultimately enable more successful and sustainable business model transformations.

Finally, it takes time for the economic value of investments in AI use to materialize. On the basis of the analyzed papers, this research corroborates the J-curve model for AI-based economic value creation (Brynjolfsson et al., 2021). Following the well-established hypothesis of delayed value creation from digital technology (Brynjolfsson, 1993), initial investment in AI may not create economic value until later stages because of the need to invest in complementary areas such as data technology, infrastructure, human resources, work processes, skills, and incentives. This knowledge is important for managers seeking to implement AI.

6. Conclusions

This research emphasizes the critical need for strategic and thoughtful AI implementation within businesses. It explains that mere possession of AI technology is insufficient for value creation. AI use can be strategic or operational. Operational use involves integrating AI into existing business processes such as production or marketing to enhance efficiency. While these efforts are vital, competitors often replicate them, and they do not provide a significant strategic advantage. In contrast, strategic AI use involves careful positioning within the business model architecture to trigger data network effects and activate customer retention themes. However, as demonstrated by the EU AIA, such integration must be supported by robust regulations addressing AI deployment's ethical and social implications. This strategic approach attracts new customers and generates vast sets of data, thereby enhancing AI-driven services. It also establishes substantial entry barriers for competitors and deters customer migration.

6.1. Limitations

This theoretical reconstruction integrates business model theory with the theory of data network effects to propose a new approach to using AI for value creation and capture. While empirical evidence supports business model theory (Massa et al., 2017; Zott et al., 2011), theories on data network effects are still evolving, presenting opportunities for empirical validation of the proposed framework.

6.2. Future Lines of Research

Ongoing studies of AI use in business models, mainly through ML, present several opportunities for future research. Studies should prioritize the expansion of the empirical base, mainly through longitudinal studies and cross-industry comparisons, to generalize findings and provide deeper insights into how AI affects various sectors and economies over time. For instance, further investigation into the dynamic interplay between AI technology and business model evolution can provide insights into how firms can consistently adapt and innovate in response to technological advancements.

Declaration of Conflicts of Interest

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