Strategic Management of AI Investments: A Dynamic Capabilities and Business Model Innovation Perspective⋆

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ABSTRACT

Artificial Intelligence (AI) promises substantial returns in organisations, motivating firms to consider AI investments to improve their businesses. The investments offer new opportunities for transforming business processes, which can increase the company's value. Despite the promise of AI to drive competitive advantage, organizations struggle to realise the value, often because of fragmented initiatives and strategic misalignment rather than technological failures. Current research often overlooks the strategic initiatives required to convert dynamic technological potential into sustained performance. This study addresses this gap by integrating Dynamic Capabilities (DC) and Business Model Innovation (BMI) theories to deconstruct the realisation of AI value. Employing a mixed-methods design, we triangulated a systematic literature review with exploratory practitioner interviews to contrast theoretical ideals with operational realities, aiming to benefit from AI investments. The findings reveal that the primary barriers to AI value realisation, strategic misalignment, organizational inertia, and technical/data limitations, are interconnected and mutually reinforcing, creating a negative feedback loop that prevents scaled impact. This systemic failure is driven by critical operational frictions, including data governance silos, leadership literacy gaps, and the inability to quantify AI value, which collectively disrupt the link between strategic intent and execution. Also, findings showed the potential of strategically interlinking Dynamic Capabilities (DC) and Business Model Innovation (BMI) for business value, where DC senses and mobilizes AI opportunities and BMI turns over adaptive capacities into value creation and capture, thus, contributing to AI value realization in organisations.

1. Introduction

The accelerating pace of digital transformation has positioned Artificial Intelligence (AI) as a central driver of competitive advantage [21]. Coupled with big data analytics, AI enables organizations to harness data to inform decision-making, enhance value propositions, optimize value chains, and innovate business models [4, 30].

Despite these promises, many organizations struggle to realize the expected benefits of AI. As noted by Babu et al., only approximately 20 percent of firms implementing AI achieve their projected outcomes. This shortfall is frequently attributed to fragmented, use-case–specific AI initiatives that lack alignment with an overarching strategic vision. Additionally, organizations frequently engage in speculative AI investments that lack demonstrable short-term business value, resulting in the misallocation of resources and opportunity costs [30]. These patterns suggest that the primary barriers to AI value realization are less technological in nature and more deeply rooted in strategic and organizational matters. Still, research on AI's technical capabilities and operational efficiencies often overlooks the strategic management required to drive a sustained competitive advantage from technological advancements [13, 11]. Addressing this requires AI integration into core organizational processes to amplify the firm's DC Gao et al.. These enhanced capabilities are absolutely foundational for realizing AI based innovation-led value creation and securing a sustainable competitive advantage.

However, significant ambiguity remains regarding how this interdependence actually unfolds to facilitate AI value realization. Although existing scholarship has examined AI adoption and strategic management separately, few studies integrate these domains to account for the persistently high failure rate of AI initiatives. In particular, the literature provides limited insight into how DC and BMI interact to address the barriers to AI value realization that consistently impede effective execution.

Our study bridges the gap by exploring the contributions of DC and BMI to addressing challenges related to strategic misalignment, organizational inertia, and data issues in implementing innovative AI solutions, allowing organisations to remain competitive in the market. The key research question driving the research was: How can DC and BMI interact to enable organisations to implement valuable AI investments? We deployed a mixed-method design to answer the research question.

The study finds that DC and BMI function as mutually dependent mechanisms that convert AI investments into sustainable competitive outcomes. Specifically, DC serves as the organizational engine for identifying, evaluating, and mobilizing AI opportunities, whereas BMI provides the mechanisms for embedding these adaptive capacities into achieving value creation and capture. This conceptualization both advances strategy scholarship and offers actionable guidance for managers seeking to translate AI investments into durable performance.

The remainder of this paper develops a holistic approach for understanding AI-driven value realization. In Section 2 we establish the background and theoretical landscape of the paper. Section 3 outlines the mixed-methods research design used to address the research question. Section 4 examines the mechanisms of value creation, synthesizing recent literature to highlight the interplay between DC and BMI. This

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section explores the dimensions of value in the AI context (Section 4.1), analyzes how AI reshapes organizational logic through novel business models (Section 4.2), and assesses the enduring barriers to value capture (Section 4.3).

Section 5 presents our empirical findings, contrasting the theoretical mechanisms identified in the review with organizational practices and real-world barriers encountered by practitioners. Finally, Section 6 integrates the synthesized literature and empirical findings to address our central research question. We conceptualize AI value realization as a dynamic, capability-enabled process of business model innovation and discuss the strategic and organizational transformations required for scalable impact, offering key theoretical and managerial implications.

2. Background

AI represents the most profound technological discontinuity since the internet, compelling a fundamental reassessment of how organizations create and sustain value. While much of the initial literature has centered on the technical specifications and operational efficiencies of AI, the true challenge lies in understanding the strategic management required to maximise value from AI investments. This background section, therefore, establishes the necessary dual foundation for our study. It first defines and categorizes the AI capabilities (Section 2.1) to specify the strategic mechanisms by which different forms of AI influence organizational processes. This categorization is crucial because the strategic impact of AI is highly dependent on its technical type. It then introduces the existing theories of value mechanisms to provide the theoretical lenses for analyzing how firms strategically deploy resources, knowledge, and capabilities to create, deliver, and capture value (Section 2.2).

2.1. Artificial Intelligence in Organizations

AI is increasingly recognized not as a single technology but as a continuum of capabilities that evolve in sophistication. At its core, AI refers to systems designed to emulate aspects of human intelligence: perceiving, learning, reasoning, and acting upon information from their environment. Unlike traditional automation, which follows preprogrammed rules, AI distinguishes itself through its ability to adapt and improve over time [6]. To conceptualize this progression, scholars and practitioners often employ hierarchical models that classify AI according to problem-solving complexity. In this paper, we group these capabilities into three categories: analytical and predictive AI, optimization and decision-making AI, and Artificial General Intelligence. The grouping helps illustrate how AI applications differ not only in technical sophistication but also in their potential to reshape organizational decision-making and strategy.

Analytical and predictive systems are designed to analyze data, identify patterns, and generate predictions. ML, a central subset of AI, enables systems to construct predictive models by learning from historical data rather than relying solely on explicit programming [30]. Within this category, deep learning represents a breakthrough, particularly

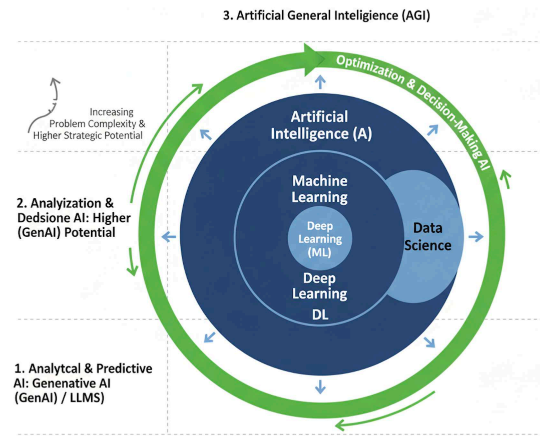


Figure 1: Strategic Classification of AI Capabilities by Problem Complexity. This diagram maps the technical architecture of AI (nested domains of ML and DL) to a three-part strategic framework. The framework highlights the progression from Analytical & Predictive Systems to more complex Optimization and Decision-Making AI , with problem complexity increasing toward the theoretical AGI level.

in tasks such as image recognition, speech processing, and natural language understanding. Drawing inspiration from the architecture of the human brain, deep learning has fueled many of the high-profile advances in AI adoption [2]. More recently, Generative AI (GenAI) has emerged as a distinctive extension of this category. Built on Large Language Model (LLM)[1], GenAI not only detects patterns but also creates new content from text and images to computer code [33]. This capability has captured significant attention in business, as it enables partial automation of creative and knowledge-intensive tasks once thought to be uniquely human.

Beyond prediction, a second category of AI focuses on decision-making and optimization. These systems combine predictive analytics with optimization techniques to determine the best possible course of action under uncertainty [15]. For example, in logistics, predictive models may anticipate delivery delays, while decision-focused AI designs optimal alternative routes to minimize cost and time. These systems represent a move from AI as an "analyst" to AI as a *strategic decision partner*, providing not just prediction but actionable recommendations. The impact of this category is especially relevant where complex trade-offs must be made under constraints of time, cost, and risk [28].

The third category, Artificial General Intelligence (AGI), remains a theoretical construct. Defined as AI with human-level reasoning, creativity, and judgment, AGI would be capable of addressing unstructured problems across multiple domains. Unlike narrow AI, which excels only within specific contexts, AGI would generalize knowledge flexibly and autonomously [6]. While AGI remains a long-term goal, the true value of current AI technologies is already being realized in a variety of business contexts.

[1] LLMs are able to generate coherent and contextually relevant language by predicting word sequences or producing novel text from prompts

Viewing AI through this three-part framework highlights that adoption is both a technical exercise and a strategic process. As Åström et al. emphasized that AI maturity is often overstated, requiring organizations to adopt a staged approach [2]. The key question for organisations is not whether to adopt AI, but which category of AI is most appropriate for a given business problem and how it aligns with organizational goals. In particular, while LLMs[2] offer unprecedented capabilities, not every use case demands cutting-edge GenAI. In many situations, simpler predictive models may deliver higher returns with a lower implementation complexity. The critical issue is therefore not which AI technologies are available, but how they can be effectively aligned and leveraged to generate measurable business value [30].

2.2. Theoretical Foundations

Maximizing the value of AI investments requires a clear understanding of how organizations deploy resources, knowledge, and capabilities to create, deliver, and capture value. Several theories related to the mechanism of value creation exist in the literature. These include Resource-Based View (RBV), which focuses on identifying resources, and Knowledge-Based View (KBV), which highlights knowledge as a resource for innovation and competitive advantage [8, 22]. Both RBV and KBV theories may contribute to highlighting AI-driven business model; however, their focus on the possession of resources and knowledge limits guidance on how organizations can adapt, integrate, and reconfigure these assets in response to changing environments. This gap is addressed by DC theory, which describes an organization's ability to sense opportunities, seize them through resource allocation, and transform operations to maintain competitiveness [36, 10, 17]. In AI-driven business models, DC explains how firms can respond to emerging technologies, anticipate market shifts, and continuously refine AI capabilities to maximize value.

Additionally, Resource Orchestration theory extends DC by operationalizing these capabilities through managerial action [31, 30]. It emphasizes structuring, bundling, and leveraging AI resources to achieve strategic goals, ensuring that sensing, seizing, and transforming capabilities translate into concrete organizational outcomes. This practical perspective bridges theory and action, guiding leaders in optimizing AI assets and aligning them with business strategy. While DC and Resource Orchestration ensure that AI capabilities are adaptable and actionable, BMI provides the strategic lens to translate these capabilities into value. BMI focuses on reconfiguring core business model elements: value proposition, value creation processes, and value capture mechanisms to leverage AI investments for new growth opportunities [23, 34]. In combination with DC, BMI ensures that organizations not only adapt to change but also innovate business models to capture maximum value from AI.

[2]LLM: Large Language Model

3. Methodology and research design

This study employs a rigorous, mixed-methods research design to examine how DC and business-model innovation interact to enable organizations to create, deliver, and capture sustainable value from AI investments. The research is grounded in a pragmatic philosophy, which prioritizes practical application and real-world relevance over theoretical abstraction [18]. This philosophical stance is particularly well-suited for this study, as it seeks to solve concrete organizational problems and generate actionable insights. Consistent with this philosophy, we integrate a Systematic Literature Review (SLR) with an exploratory interview study. The SLR provides a theoretically grounded understanding of current knowledge, while the interviews offer practice-oriented insights into how these mechanisms manifest in reality.

To address the research question, the study employs an abductive approach, enabling an iterative process of moving between empirical data (interviews and document reviews) and theoretical insights from the literature [9]. This integration of perspectives supports the development of a conceptual frameworks informed by established theory and practical realities, aligning with the pragmatic philosophy that emphasizes applying research findings in real-world contexts.

3.1. Systematic Literature Review

To develop a consolidated evidence base, we conducted a systematic literature review (SLR) addressing the question:*How do DC and business-model innovation interact to enable organizations to create, deliver, and capture sustainable value from AI investments?*. The review followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines for transparency and reproducibility [24] and was structured using the Population, Intervention, Comparison, Outcome, Context (PICOC) framework to clarify scope and eligibility criteria [25].

The PICOC framework allowed for structuring research questions by breaking them down into five components: population, intervention, context, objective, and comparison. In this context, the target population comprises industries and businesses actively engaging in AI investments. The intervention analyzed involves strategic and organizational mechanisms, particularly DC and BMI, that enable value realization from AI. The study's context revolves around generating business value within diverse, data-driven, and agile organizational environments. No explicit comparison group was used, to maintain an exploratory focus, concentrating solely on the mechanisms for maximizing AI value rather than contrasting AI with other technologies. Instead, our primary objective is to synthesize evidence on how DC and BMI interact to overcome barriers and translate AI investments into a sustainable competitive advantage.

A comprehensive search was conducted in Scopus and Web of Science, targeting peer-reviewed journal articles published between 2013 and 2024 a period reflecting the formal emergence of Industry 4.0 and rapid proliferation of

AI technologies. The search string (Appendix A) combined terms related to AI, value creation, organizational capabilities, business-model innovation, and agility.

The search yielded 1,406 records. After removing duplicates (n = 148), 1,258 titles and abstracts were screened using predefined inclusion criteria (peer-reviewed, English, relevance to AI and organizational value). A total of 76 articles were retained for full-text assessment. Quality appraisal (rigor, transparency, methodological fit, conceptual clarity) resulted in 23 high-quality studies included for synthesis.

3.2. Exploratory Interviews

To complement the conceptual insights from the literature and capture contemporary organizational practices, we conducted an exploratory interview study. This qualitative component aims to bridge the gap between theoretical constructs and real-world experiences. Specifically, the interviews were designed to: (1) validate and contrast themes emerging from the SLR; (2) uncover practical challenges not visible in published research; and (3) refine the integrative framework of AI value realization.

A combined purposive and snowball sampling strategy was used to recruit practitioners directly involved in AI value realization [20]. Purposive sampling ensured the inclusion of participants with significant decision-making power, such as Principal Data Scientists, Portfolio Managers, and Vice Presidents. While the sample size was eleven ($n = 11$), the high level of expertise among participants allowed for deep insight into strategic mechanisms, and data collection ceased once theoretical saturation was observed.

Semi-structured interviews were conducted between May–July 2024, each lasting 45–60 minutes.This method was selected due to its flexibility in exploring complex issues and eliciting rich, in-depth data [40]. As highlighted by [12], qualitative interviews are crucial for capturing expert knowledge and opinions, enabling comprehensive exploration of participants' experiences and perspectives.

The interview guide adhering to best practices outlined in [19], was structured around themes identified in the SLR, including capability development, value capture mechanisms, organizational barriers, and business-model implications. All interviews were audio-recorded and transcribed verbatim.

Interview transcripts were analyzed using reflexive thematic analysis, following a three-stage, iterative procedure [19, 9]. First, an initial coding phase involved systematically labeling text segments to identify concepts, recurring patterns, and participant-driven insights. Second, related codes were clustered into higher-order themes that captured broader conceptual categories emerging across interviews. Finally, these higher-order themes were integrated into aggregate dimensions aligned with the research questions and informed by insights from the systematic literature review. This iterative approach facilitated ongoing refinement and triangulation between practitioner accounts and the established literature, thereby enhancing both the theoretical grounding and practical relevance of the findings.

4. AI Value Mechanisms

As AI becomes increasingly embedded in organizational strategy and operations, understanding how it generates value is both a theoretical and practical imperative. The mechanisms through which AI creates, delivers, and captures value are complex and multifaceted, shaped by technological capabilities, organizational structures, and evolving market dynamics. To address the research question of how dynamic capabilities DC and BMI interact to enable organizations to create, deliver, and capture sustainable value from AI investments, this section synthesizes insights from the literature. It begins by unpacking the core dimensions of value in the context of AI (Section 4.1), then Section 4.2 explores how AI-driven BMI reconfigures organizational logic, and finally examines the persistent challenges organizations face in realizing the full potential of AI (Section 4.3).

4.1. Value dimensions

To understand how organizations realize value from AI, it is essential to first analyze the fundamental dimensions of value itself. Effective AI integration requires a well-defined business model, guiding processes and operations to ensure long-term viability. A business model acts as the basic framework that governs resource allocation and stakeholder collaboration within an organization [41]. Grounded on principles such as operational efficiency, comprehensive stakeholder ecosystems, and clarity on mutual contributions, the models structure organizational activities, including a series of actions to create, deliver, and monetize value [32, 1]. Thus, business models, beyond their structural role, serve as the cornerstone of the value mechanism. Drawing primarily on Osterwalder et al. framework, the studies converge on three interrelated dimensions: value creation, value delivery, and value capture [23, 1].

Value creation is increasingly understood as a deliberate, resource-intensive process that relies on aligning strategic capabilities with customer-centric activities to achieve organizational objectives [30, 41]. A dominant finding across the reviewed studies on value creation, particularly in the context of AI implementation, underscores a fundamental paradigm shift. Value creation is no longer a unidirectional offering from firms to customers, but rather a dynamic process of value co-creation embedded within networks and collaborative ecosystems [27, 30, 41].

Effective value co-creation requires organizations to embed collaboration into their core strategy, engaging stakeholders in co-designing AI-driven solutions that deliver differentiated, mutually beneficial outcomes. Central to this process are trust, transparency, and effective communication, which serve as the relational foundations for successful and sustainable co-creation [30, 41]. Building on these foundation, AI shifts the traditional notion of value delivery toward ecosystem facilitation, where firms act less as providers of final outputs and more as orchestrators of co-creation.

Practically, this reorientation demands a reconfigured operating model that translates the AI-driven value proposition into action by establishing digital platforms, data

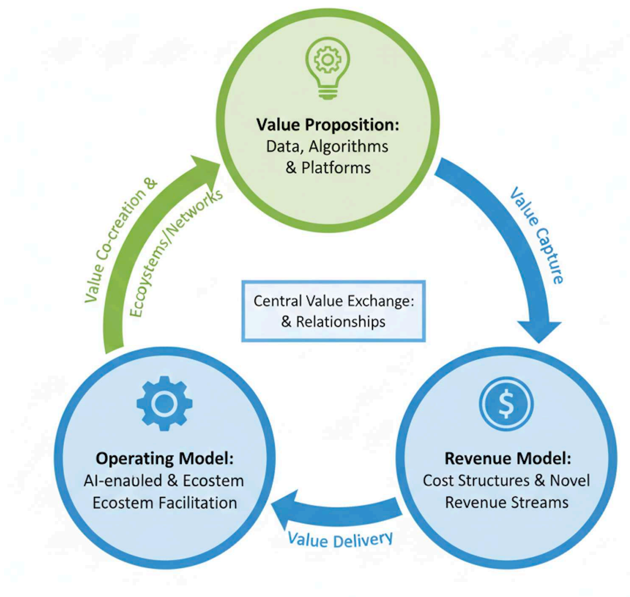


Figure 2: AI-Driven Value Mechanisms. This figure illustrates how AI reconfigures the fundamental dimensions of value creation, delivery, and capture. It depicts the shift from traditional business model components to AI-enabled processes, emphasizing value co-creation, ecosystem facilitation, and the expanded value proposition to include data, algorithms, and platforms.

pipelines, and governance structures to support collaboration [30]. Rather than functioning through closed, linear processes, an AI-enabled operating model operates as a co-creative platform in which activities such as data sharing, continuous feedback loops, and stakeholder engagement are integral [41]. These mechanisms not only strengthen collaborative relationships but also ensure that AI solutions remain adaptive, trustworthy, and responsive to evolving needs.

On the other hand, collaborative value creation alone is insufficient; AI business models must secure a share of the benefits generated to enable reinvestment and sustained competitiveness [38, 27, 7]. Focusing on value creation only hinders the long-term success and sustainability of the organization as it concentrates on customer satisfaction, overlooking benefits needed to sustain operations, i.e., internal value capture [38]. Researchers define value capture as the process through which firms secure profits from business activities to achieve a competitive advantage [27] and ensure economic returns and equitable profit distribution [6], thereby promoting sustainability and fueling further investment [38].

The value capture process is governed by the revenue model, which dictates the firm's specific strategy for generating income (revenue streams) and managing expenses (cost structure) to equitably capture a portion of the co-created value, ensuring sustainable reinvestment back into the collaborative ecosystem. However, the literature highlights a persistent tension: an excessive emphasis on capture can stifle the innovation and ongoing co-creation that are essential for AI-driven value generation [32]. Consequently, firms are challenged to optimize cost structures, discover novel revenue streams, and preserve financial viability, while carefully balancing appropriation with the collaborative innovation that underpins long-term success.

Balancing value creation and capture requires value proposition, which serves as the integrative bridge between creation and capture, articulating the benefits offered to customers and the portion appropriated by the firm [41, 30, 23]. Beyond differentiation, it facilitates coordination across internal units and external partners, aligning stakeholders around a shared vision [41]. Traditionally, a value proposition centers on a static product or service, like a physical good or a fixed consulting service. AI fundamentally extends this dimension beyond products or services to include data, algorithms, and platforms [29]. Effectively communicating these AI-enabled benefits supports premium pricing, sustainable revenue streams, and competitive advantage. While predictive capabilities allow firms to influence customer value-creation drivers, ethical and strategic tensions surrounding data use require careful management to avoid reputational risks.

4.2. AI Business Model Innovation (AI-BMI)

Drawing from the integrated framework of value co-creation, facilitation, and capture, it becomes evident that traditional business models, often perceived as fixed and static; struggle to accommodate the dynamic requirements of AI. While the integrated framework clarifies how AI can unlock sustainable advantage, its disruptive nature challenges static business models, necessitating business model innovation BMI. AI reshapes how value is created, delivered, and captured, demanding DC to adapt and thrive [2, 32].

BMI refers to unique and significant change of components or relationships within business models [2] to generate, deliver and capture benefits in novel ways [1]. Consequently, AI-BMI emerges as a critical mechanism for organizations to continuously generate and sustain value. The literature defines AI-BMI as the deliberate, novel, and significant modification of core business model components or their interrelationships, achieved through rethinking operations to leverage AI technology [2, 1]. This involves developing new strategies for creating, delivering, and capturing value, supported by comprehensive market analysis, capability development, and risk management [27, 2]. To operationalize AI-BMI, firms must leverage their DC organizational competencies that enable adaptation in volatile environments [34]. These capabilities manifest through a series of strategic activities as summarized in Table 1.

A central driver of AI-BMI is the redefinition of the value proposition and heightened engagement with its broader ecosystem; customers, partners, and stakeholders. Studies indicate that compelling AI-enabled value propositions significantly enhance firm performance [41, 26]. Leveraging AI's predictive and cognitive capabilities allows organizations to anticipate and influence customer behavior, enabling

Table 1
Steps in AI Business Model Innovation

Step	Description
Market need identification	Thoroughly understand market needs, challenges, pain points, opportunities, and unmet customer expectations that AI can address.
AI Integration Strategy Development	Develop a clear AI integration strategy aligned with organizational goals. Assess current processes, focus on decision-making support, and plan for the long term.
Exploratory and experimental approach	Adopt an exploratory and experimental approach to AI innovation. Test and combine various initiatives to jointly produce value, learning from successes and failures.
Systematic and comprehensive approaches	Use systematic and comprehensive approaches to AI integration. Utilize data and analytics, balance market-pull and technology-pull strategies, and maintain a customer-centric focus.
Ecosystem reconfiguration and resilience midrule Rapid time to market	Consider the ecosystem dimension. Reconfigure and create ecosystem resilience, understanding AI's impact on relationships with partners, suppliers, and stakeholders. Prioritize rapid time to market. Ensure quick and effective introduction of AI-enabled value propositions. Leverage technology advancements and adapt business processes for rapid innovation.
Complementary capabilities Development	Develop complementary capabilities supporting effective AI implementation. This may include data analytics, talent management, and organizational culture changes.
Continuously measure and refine the strategy	Continuously measure the impact of AI initiatives and refine the strategy based on the learnings. Adapt and adjust the approach as needed to maximize the value derived from AI investments.

innovative offerings that extend beyond traditional product ownership [26]. This approach requires market-driven AI innovation, emphasizing tangible customer benefits and the design of relevant, differentiated products and services [27, 22]. Equally important is the orchestration of interactions within complex ecosystems. Organizations must prioritize ecosystem reconfiguration and resilience, understanding how AI reshapes relationships with partners, suppliers, and other stakeholders [22, 7]. As a result, AI BMIs are imperative for organisations to remain competitive in the market through identifying new opportunities and sieze them for business growth while meeting customer needs.

Successful integration necessitates a tailored AI strategy that evaluates existing processes and plans for long-term ecosystem alignment [5, 22]. Accordingly, AI-BMI demands strategic agility and continuous capability development. Firms must adopt an exploratory, experimental approach, testing and combining initiatives to co-produce value [29]. Achieving this requires balancing market-pull and technology-pull strategies, developing complementary capabilities such as data analytics and talent management, and maintaining rapid time-to-market to ensure the swift introduction of AI-enabled offerings. Thus, AI-BMI serves as the strategic outcome of a firm's DC. It represents the successful re-configuration of the business model to seize new opportunities, thereby ensuring that value creation translates into a sustainable competitive advantage.

4.3. Constraints on AI-enabled value capture

Despite the growing interest around AI's transformative potential, realizing its full value remains a complex challenge. While the previous (Section 4) outlined the mechanisms through which AI can create, deliver, and capture value, this section shifts focus to the barriers that hinder these outcomes. The literature indicates that impactful implementation of AI is often constrained by a number of interrelated strategic, organizational, and technical challenges. These constraints not only limit scalability but also prevent firms from embedding AI into their core value logic.

A central and recurring pitfall is strategic misalignment [2, 41, 30]. Without a coherent strategy that explicitly links AI initiatives to business objectives, projects frequently remain isolated experiments that fail to generate sustained value. The literature emphasizes the importance of articulating AI contribution in an organisation to value co-creation, facilitation, and capture, and ensuring alignment with the broader business model. Such strategic clarity is essential not only to guide implementation but also to legitimize resource allocation and sustain commitment at scale.

These strategic shortcomings are closely tied to organizational barriers. Effective AI adoption requires significant transformation in process design, workforce capabilities, and cultural orientation [26]. Resistance to change, fueled by concerns about automation and job displacement, often impedes progress. Leadership plays a critical role in mitigating these anxieties by fostering a culture of continuous learning and adaptability. As a result, leadership acceptance and willingness is imperative to support AI investment agenda at the strategic and organisational levels.

Furthermore, firms frequently face challenges in aligning resources, balancing short-term operational needs with long-term strategic investments, and ensuring initiatives are adequately staffed and supported [41]. These challenges are amplified by the DC that emerge from AI integration, which push organizations toward adaptive, AI-enabled business models to remain competitive. However, the extant literature offers limited practical guidance on how to design, govern, and scale such dynamic models.

Equally significant are technical and data limitations, which underpin many failed AI initiatives. The most pervasive challenge is data quality, as poor, fragmented, or siloed data sets undermine model reliability and increase preprocessing costs [2, 22, 39]. Beyond data, firms struggle with inadequate infrastructure and inconsistent technical standards, which limit interoperability and scalability [29]. AI integration requires a well established infrastructure with defined standards to ease processes such as data sharing and exchange. Therefore, building robust technical capabilities that can accommodate dynamic changes for organisations to thrive is imperative.

Additionally, weak governance and ethical frameworks further exacerbate risks, exposing organizations to compliance failures and reputational harm, and thereby eroding trust in AI systems [30, 27]. Such frameworks should be tailored based on the organisational context benchmarking national and international frameworks. Again, the establishment of these frameworks requires strategic support and willingness from leaders. Also, skills and competence to design governance measures that will adapt to the continuous change in AI-BMI are critical.

Taken together, the literature underscores that realizing value from AI is not simply a technological challenge but a multidimensional problem embedded in strategy, organization, and technology. As illustrated in Fig. 3, these barriers are interdependent, creating a reinforcing cycle that constrains progress. Strategic misalignment exacerbates technical challenges, which in turn weaken organizational readiness, further eroding strategic clarity. Overcoming these barriers requires organizations to move beyond isolated pilot AI projects toward sustained, organisation-wide impact.

5. Results from the Interviews

The empirical study was designed to complement the findings of the literature review. We aimed to explore the concept of value mechanisms and associated challenges from AI practitioners. The results and findings of the interviews are presented in the following themes.

5.1. Theme-1: AI value realisation

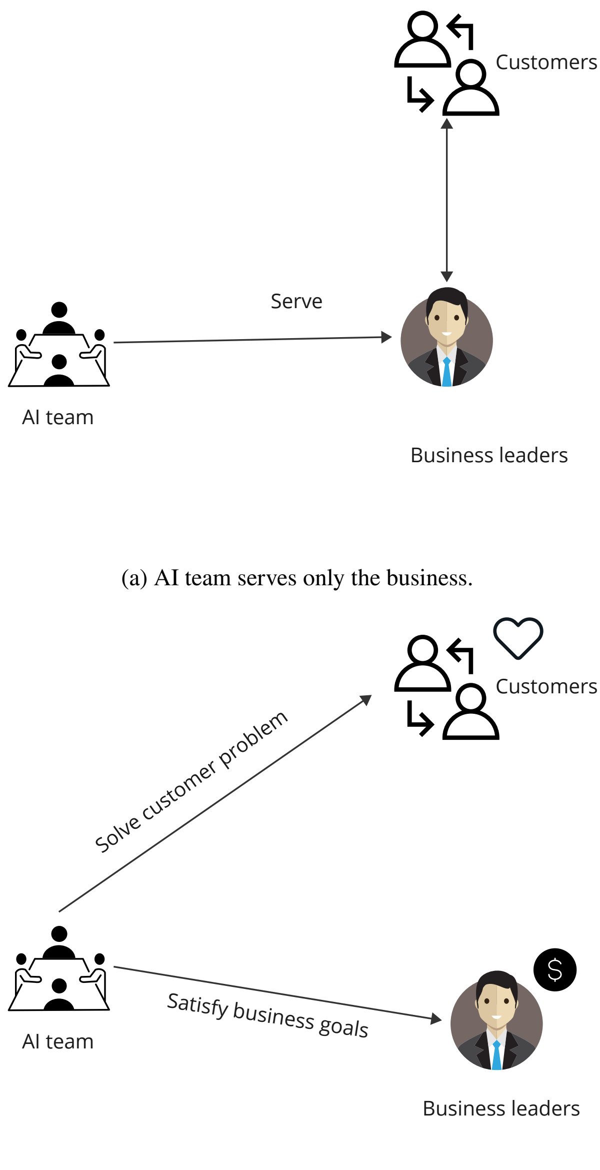
5.2. AI value co-creation

Our study explored the concepts of customer value orientation and interaction as key drivers of AI value co-creation. All respondents emphasized the importance of customer-centric innovation to promote scalability for AI value maximization in the organization. According to them, a deep understanding of customer pain points is crucial for developing resonant AI solutions. The results showed that customers' needs are identified and observed throughout the AI project lifecycle. Practitioners employ several practices, including in-depth user research, discovery phases, and iterative development informed by continuous feedback to engage customers in the process. One respondent noted,

Figure 3: Interconnected Challenges in Maximizing AI Value. This figure depicts the feedback loop between Strategic Misalignment, Organizational Barriers, and Technical/Data Limitations. Rather than isolated obstacles, these challenges interact dynamically, perpetuating the gap between pilot projects and scaled business impact.

"We typically initiate an exploration phase with the customer to discern their desired outcomes." Ultimately, these insights establish sustained engagement and direct customer interaction as the defining essence of AI value co-creation, necessary to avoid misalignment and deliver solutions that genuinely resonate with customer needs.

To explore the operationalization of this engagement, we asked respondents what steps can be taken to ensure AI innovation reflects the needs of customers and drives both customer and organizational value. All respondents underlined the critical role of customer feedback in driving continuous product improvement and innovation. One respondent noted, *"The strategy is to develop and implement small features incrementally while addressing customer feedback".* Another respondent highlighted the importance of setting clear expectations and delivering simple, understandable outcomes initially: *"Setting clear expectations and delivering simple, understandable outcomes initially is crucial. We learned to bring customers along every step of the way, ensuring their needs are met without overwhelming them with data."* These statements highlight the importance of gradual development and disciplined iteration informed by customer feedback. This continuous, risk-mitigating approach ensures that the final product is highly fit-for-purpose, driving rapid user adoption and minimizing costly post-launch rework. Consequently, this iterative cycle is essential for maximizing AI value realization by directly promoting the scalability and efficient integration of the solution across the organization.



(a) AI team serves only the business.

(b) Ideal model: Customer and business engagement.

Figure 4: Comparison of AI Team Orientation Models: a illustrates a situation where the AI team does not have direct contact with customers and serves only the business. b shows the ideal model where the AI team maintains constant engagement with both customers and the business.

However, respondents iterated the lack of direct connection with customers, often relying solely on the business side to inform them. This can lead to misalignment between customer needs and AI solutions, shifting focus from outcomes to features, and reacting to internal pressures rather than external demands. For instance, a respondent noted, *"... we rely on the business side to inform us about the end customer's needs and the expected revenue. Ideally, we should interact directly with the end customers, as indirect information has not always been dependable."* This highlights the importance of establishing direct customer feedback channels to ensure AI development is grounded in real-world needs. Achieving the right balance, as illustrated in Fig. 4b, requires organisations to shift from reacting to internal pressures by prioritising customer needs and insights to proactively identifying and solving the most critical customer problems.

5.3. AI value capture

The findings further highlight the difficulties in articulating a compelling AI value proposition. This challenge is rooted in the reliance on business intermediaries, which creates channel dependence and distorts the voice of the customer, leading to AI solutions that frequently lack product-market fit and jeopardizing commercial viability. Compounding this issue is the limited involvement of the AI team in strategic positioning, resulting in propositions that do not accurately reflect technical utility or customer need. To address these gaps, respondents advocated for direct customer engagement and collaborative prioritization exercises, such as feature ranking and hypothetical budgeting, to ensure the propositions reflect real customer needs and strategic objectives. A strategic approach from AI product conception to post-market analysis is essential to ensure that AI initiatives deliver tangible value and contribute meaningfully to overall business objectives.

Beyond the articulation of the value proposition, another strategic approach for maximizing AI value is the ability to robustly quantify and communicate the returns on investment. Accordingly, respondents were asked about their organizational processes for effective measurement, a prerequisite for securing ongoing support and realizing AI's full potential. Seven respondents highlighted the difficulties organisations face in measuring value from AI investments. According to them, organizations often struggle to quantify the impact of AI initiatives and demonstrate return on investment. This is due to several factors, including difficulties in defining actionable metrics, attributing outcomes to AI, and translating technical insights into business benefits. Respondents further pointed to the lack of tailored metrics for different deployment contexts: *"We need better mechanisms to measure success for on-prem products"* and the difficulty of translating technical achievements into business-relevant outcomes: *"The biggest challenge is quantifying the value and impact of our work .... we faced difficulties due to skill set limitations."* Also, the interviews highlighted a disconnect between business and AI teams, which complicates the definition and tracking of relevant KPIs.

Several approaches are proposed to enable organisations measure AI value and impact. Eight respondents emphasized the importance of early planning, where metrics should be captured from day one. Everyone in the team should understand and follow the process for creating and capturing value. Additionally, nine respondents urged starting small while assessing whether the proposed AI innovation serves customer needs and generates value. One respondent pointed out, *"Setting clear expectations and delivering simple, understandable outcomes initially is crucial."* These approaches are imperative for measuring AI impact on both the customer and the organisation.

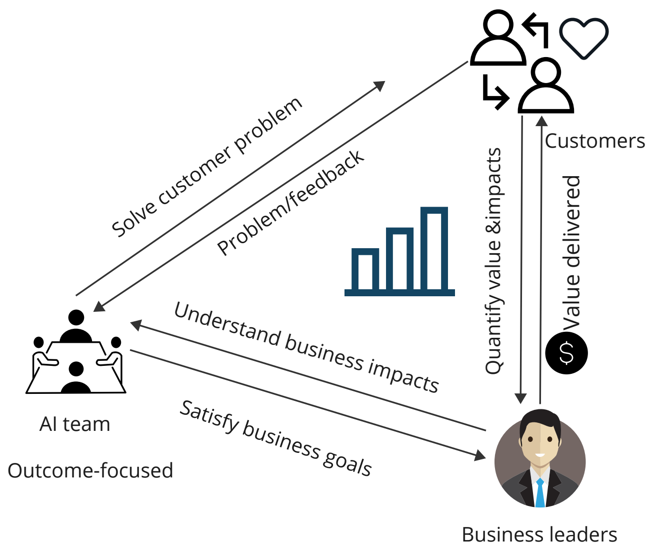


Figure 5: Effective collaboration between the AI team, business, and customers is vital for aligning AI initiatives with overall business objectives and delivering tangible value.

Ultimately, organizations are encouraged to establish clear, actionable metrics and effectively communicate AI benefits to secure ongoing support. Bridging the gap between business units and AI teams is crucial for developing a shared understanding of problems and accurately measuring AI impact as illustrated in Fig. 5

5.4. Theme 2: Leadership and organisation development

We further explored the contribution of organizational and leadership strength to implementing valuable AI solutions among the respondents. All respondents consistently emphasized the importance of effective leadership in aligning AI initiatives with business strategy, managing risks, and fostering collaboration, while also acknowledging the challenges associated with achieving such leadership. One respondent noted, *"We need the right skill sets to define, measure, and demonstrate value and impact effectively,"* underscoring the role of leadership in translating strategic priorities into measurable outcomes. Leadership was also seen as pivotal in bridging the gap between technical and business teams, ensuring that AI initiatives are not only technically sound but also strategically relevant. One respondent noted: *"Leaders must engage in every facet of AI planning to ensure initiatives deliver measurable value."* This calls for leadership support to provide strategic alignment and manage dynamic change, thereby seizing opportunities and generating value from AI investments.

Additionally, five respondents highlighted that a lack of innovation culture presents a significant challenge to AI value maximization. As one respondent stated, *"Organizational culture is key. We need to foster a culture of innovation and continuous learning,"* calling for a leadership style that promotes experimentation while allowing teams to challenge the status quo. Fostering this culture is not merely about acquiring new knowledge; it requires constantly challenging assumptions, encouraging new ideas, and improving internal practices: *"We need to continually check ourselves and challenge assumptions."* Supporting these practices neccesiates continuous development through training and skill enhancement. Respondents emphasized a focus on identifying learning opportunities in each project to extend practitioner skills, noting that while *"Strong data science skills are obviously important, but so is the ability to deploy and scale solutions."* These findings suggest that value delivery depends not only on the technological infrastructure but also on human-centric strategies and cultural adaptability to sense and seize emergent AI opportunities that generate value.

Furthermore, results reinforced the importance of collaboration and organizational readiness in delivering value, highlighting the dual role of external partnerships and internal cohesion. *"Collaboration and leveraging insights from AI are crucial for our future growth,"* one respondent stated. Seven respondents noted that external partners primarily support organizations by offering specialized expertise and resources to accomplish complex AI projects. Concurrently, internal collaboration is vital for cohesive teamwork and effective resource allocation: *"Expanding the team with skilled personnel supports the development and implementation of AI projects,"* and *"Having a solid connection with the business team is also important."* These responses underscore the contribution of both external and internal collaboration to designing impactful AI solutions.

In the same line, eight respondents revealed collaboration hurdles in creating value from AI investments, including undefined partnerships, a lack of standards or frameworks guiding collaborations, unclear collaboration goals, and uneven AI knowledge and literacy among stakeholders. Respondents emphasized that successful AI implementation requires both external partnerships and internal cohesion. Therefore, it is essential for organisations to invest in external and internal collaboration to be able to adapt to change and innovate business models to maximise the value of AI initiatives.

5.5. Theme 3: Data and AI strategy

Following the emphasis on organizational readiness, respondents consistently highlighted the fundamental role of robust data management and governance as the critical infrastructural enabler for effective AI solutions. Interviewees underscored that clean, accessible, and secure data is essential, yet often underestimated by leadership who don't understand the process. This gap frequently leads to technical misdiagnosis as reported by nine respondents who indicated that data engineering challenges are often mistaken for data science problems. One interviewee illustrated this by stating, *"Companies felt they had a data science problem and hired* *data scientists, but often the bigger problem is a data engineering problem."* Such misalignment reflects deeper strategic disconnects and highlights the need for organizations to both strengthen data governance frameworks through clear data accessibility, ownership, security protocols, compliance standards and address skill gaps in data transformation.

Beyond these infrastructural requirements, respondents emphasized that aligning data and AI strategies with overarching business objectives is equally critical for AI success. While many organizations recognize the importance of data, formalizing comprehensive data and AI strategies remains a persistent challenge. As one participant noted, *"Align business strategy with data and AI strategy. A data driven business strategy should consistently and continuously explore and analyse data to extract valuable insights."* Another respondent stated, "We have prerequisites like data strategy and governance in place, but we need to formalise these processes and ensure they are followed consistently." Yet, institutionalizing these practices is difficult. Therefore, it is essential for foundational governance and strategic alignment conditions to be in place to enable organizations realize tangible AI value.

Apart from the data governance, respondents underscored the importance of leveraging analytics for internal efficiencies as an initial and highly impactful step in realizing value from AI investment. As one interviewee remarked, *"Many things we work on as consumer-facing products have applications within the organisation. For example, optimising how we run our factories."* Focusing first on internal efficiency use cases allows organizations to generate quick wins, validate solutions, and build the operational experience necessary for more complex external applications. Thus, allowing organisations to measure value from AI investment internally and scale the investment to capture and generate value from other stakeholders

6. Discussion

The effective creation, delivery, and capture of sustainable value from AI investments is fundamentally an organizational challenge that requires a strategic approach to enable business processes to embrace innovation and manage dynamic change. This study addresses the research question: *how do DC and BMI interact to enable organizations to create, deliver, and capture sustainable value from AI investments?*. Our findings show that realizing value from AI requires more than deploying technology; it demands strategic alignment and organizational transformation supported by the continuous interplay of DC and BMI.

6.1. Synthesis of findings

The interview findings align closely with existing literature and collectively illuminate how organizations struggle and occasionally succeed in achieving sustainable value creation, delivery, and capture from their AI investment portfolio. Research by Zhang et al. and Shollo et al. highlights the importance of aligning strategic capabilities with the dynamic value-creation requirements. Our interviews substantiate these insights, revealing that many AI initiatives are developed without clear business alignment. As a result, technically strong solutions often fail to address real customer or organizational needs, leading to limited value realization.

A consistent theme across interviews is the centrality of customer-centricity in AI value creation. Despite advances in AI technologies, organizations frequently fail to integrate customer needs into AI development processes. This disconnect echoes the literature, where Verdin et al. and Åström et al. emphasize that value emerges not from technical novelty but from solving customer pain points. Interviewees confirmed this, noting that many AI solutions are deployed without ongoing customer feedback, resulting in limited market relevance. Thus, the crucial sensing capability, the initial phase of the DC framework requires structured customer discovery and iterative engagement to ensure the value proposition pillar of the BMI is correctly defined.

Leadership and collaboration emerge as critical determinants of whether firms can seize AI opportunities. Both literature and practitioners highlight that leaders must possess sufficient AI literacy to bridge the gap between technical potential and business relevance. Leadership drives not just strategic alignment but also cultural change, risk mitigation, and continuous adaptation. As a result, it is essential to have a leadership sytle that promotes innovation culture. Findings show that organisational adaptability and transformation through ongoing training, experimentation, and openness to new ideas, support the integration and scaling of AI technologies.

Interviews further revealed that many organizations still operate in silos, with weak collaboration between data, IT, and business units. This limits the organization's ability to integrate AI into existing processes or scale successful pilots. Studies by Ritala et al. and Page et al. similarly emphasize that successful seizing relies on cross-functional teamwork and learning cultures to effectively mobilize resources and commit to the value co-creation component of the BMI.

A notable contribution of our findings concerns data governance, which appears as both an enabler and a barrier across all phases of value realization. Empirical insights reinforce and elaborate on the literature's emphasis on data-related challenges resulting from a failure to formalize comprehenisve data and AI strategies. Practitioners described fragmented data landscapes, inconsistent data quality, and limited access to shared data assets, resulting in AI solutions that cannot scale or generalize. These insights reinforce literature emphasizing that failures in data governance result in misaligned AI strategies, inadequate stewardship, and weak foundations for AI-enabled business-model innovation [2, 29]. Effective value delivery depends not only on technical infrastructure but also on coordinated governance frameworks, standardized processes, and human-centric approaches to data management, requiring a constant need for organizational transformation.

The interviews also reveal persistent challenges in developing compelling AI value propositions, quantifying the impact of AI, and communicating benefits effectively. These challenges hinder value capture and signal a breakdown in the transforming capability. Transformation is essential for sustaining AI-enabled business models through continuous renewal and reconfiguration. This struggle aligns with Ritala et al. and Zhang et al., who emphasize that flexible measurement systems and clear narratives are essential for demonstrating AI's Return On Investment (ROI). Practitioners stressed that misalignment between business and AI teams further complicates this process, underscoring that the transforming capability requires joint decision-making and integrated performance frameworks to formalize governance and measurement routines necessary for the long-term value capture pillar of the BMI.

6.2. The DC-BMI Interplay: A Conceptual Framework

The necessity of leveraging both DC and BMI for effective AI value realization is conclusively demonstrated by the theoretical and empirical findings. Realizing value from an AI investment requires more than mere technological acquisition; it demands strategic alignment and fundamental organizational transformation supported by the continuous interplay between DC and BMI.

The relationship between these two theoretical constructs is interdependent and mutually reinforcing, as articulated by Teece [35]. Our analysis confirms this essential synergy: DC provides the organizational agility necessary to proactively recognize and mobilize resources for emerging AI-driven opportunities, while BMI serves as the operational mechanism that embeds those adaptive capacities into tangible frameworks for value creation and capture.

The literature highlights three mutually reinforcing barriers: strategic misalignment, organizational rigidity, and technical/data constraints that underscore the need for strong DC. Strategic misalignment reflects weaknesses in sensing and seizing: firms misread AI opportunities or fail to mobilize resources, producing initiatives disconnected from core objectives [41]. This calls for DC, which can support organisation in identifying opportunities to achieve strategic goals through AI investments.

Organizational inertia, including rigid structures, cultural resistance, leadership gaps, and skills shortages, signals a breakdown in the transforming capability as firms struggle to reconfigure processes, workforce competencies, and governance to accommodate AI. Teece [35] stresses that transformation must be semi-continuous and leadership-driven. According to Haefner et al. [16], the payoff from AI depends less on technological deployment than on organizational readiness, its structures, culture, and capacity for human–AI orchestration. Achieving such an organisational nature demand reskilling, governance redesign, and a culture of learning, calling for capabilities to sense and seize wide changing opportunities. As a result, DC can enable organisations to oversee and adapt new areas on capacity building and governance measures essential for companies to remain competitive. Still, transformation delivers limited benefits unless accompanied by BMI that rethinks value propositions, revenue models, and delivery mechanisms.

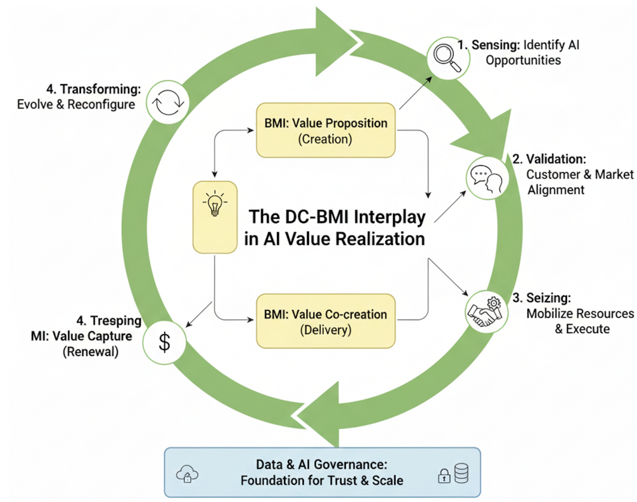


Figure 6: The DC-BMI interplay for sustainable AI value realization. This figure illustrates the dynamic interplay between Dynamic Capabilities (DC) and Business Model Innovation (BMI) in achieving sustainable value from AI investments. It depicts an iterative cycle of DC (Sensing, Seizing, and Transforming) that continuously shaped by BMI pillars (Value Proposition, Value Co-creation, and Value Capture), all underpinned by essential Data and AI Governance.

Fragmented datasets, limited infrastructure, and poor interoperability, which limit AI investments, require strong transformation capabilities to reconfigure technological architectures [2, 29]. For smaller firms, these constraints are amplified by data and scale asymmetries that favor large, data rich competitors. This calls for defined data governance approaches to manage the operational complexities involved in the data stewardship related to AI investment.Babina et al. [3] show that AI gains concentration in firms with extensive data and the capacity to scale solutions across markets. Smaller firms, therefore, often benefit from BMI strategies such as partnerships, data-sharing alliances, or participation in digital ecosystems to secure data access and achieve defensible scale. These strategies complement DC by enabling firms to leverage adaptive capacities into tangible value creation despite data and scale constraints.

Collectively, these barriers indicate that DC are necessary in addressing organisational and data related challenges but insufficient in ensuring value from AI investement. The DC lens explains how firms develop the adaptive capacity to pursue AI opportunities, but it does not fully account for the mechanisms through which that capacity is converted into market impact. BMI addresses this gap by redesigning value propositions, operating models, and revenue mechanisms so that adaptive capabilities yield measurable outcomes. As a result, BMI increases the likelihood that adaptive capacities are translated into measurable value and sustainable competitive advantage.

Similarly, AI adoption frequently demands collaboration with customers, partners, and regulators, requiring new delivery channels and shared governance arrangements that extend beyond traditional organizational boundaries. Our analysis shows that sustainable, AI-value advantage depends on the mutually reinforcing dimensions of co-creation, facilitation, and capture (Fig. 2). Achieving balance among these dimensions, particularly between value creation and value capture, is critical to maintaining stakeholder trust while securing returns, reflecting Teece [35]'s view that dynamically capable firms continuously implement, test, and refine novel business models. This necessiates the integration of AI Business Model Innovation with DC to address value mechanisms of AI investments.

The literature on AI-enabled BMI further specifies how firms reconfigure these components through AI technologies [2, 1], emphasizing the role of the sensing, seizing, and transforming imperatives that underlie DC [34]. Through sensing, firms identify emerging opportunities and evolving customer needs; through seizing, they mobilize resources and accelerate time-to-market; and through transforming, they renew structures, processes, and ecosystems to sustain competitive advantage. Together, these activities operationalize the connections between co-creation, facilitation, and capture, providing a practical pathway-from market-need identification and AI integration strategies to ecosystem reconfiguration and continuous refinement-by which DC are converted into sustainable value creation and capture.

6.3. Implications for theory and practice

Building on the mechanisms identified in this study, the findings suggest that AI adoption functions not merely as a technological initiative but as a strategic organizational transformation. For theory, this highlights the value of examining DC and BMI as interconnected processes AI contexts. For practice, findings indicate that aligning DC with BMI may facilitate sustainable competitive advantage and more effective AI value realization. We therefore structure our advice around the three core DC imperatives.

Focusing on strategic alignment, AI initiatives appear to generate the most value when they are grounded in validated market realities rather than speculative experimentation. The sensing capability is essential here as it defines the optimal BMI value proposition for the AI solution. Organizations that demonstrate stronger sensing capabilities tend to develop clear AI value propositions, integrate market intelligence into strategic decision-making, and engage directly with end customers to validate opportunities. Observations suggest that when strategic leadership emphasizes an organization wide AI value thesis and cultivates AI literacy among non-technical leaders, alignment between technical feasibility and market needs is strengthened, reducing the risk of initiatives disconnected from core business value.

Following the identification of viable opportunities, the study indicates that the ability to seize AI opportunities is fundamentally influenced by organizational design, cross-functional collaboration, and the availability of integrated data resources. DC seizing directly enables the BMI value co-creation pillar by mobilizing the necessary internal and external resources for successful execution. Firms with cross-functional AI units, shared KPIs linking technical outputs to business outcomes, and robust data governance structures tend to achieve more coherent value co-creation. In addition, extending organizational boundaries through partnerships, data-sharing alliances, or platform participation appears to provide access to specialized resources and data scale that can amplify the impact of AI initiatives, particularly for organizations with internal resource constraints.

To ensure the sustainability of seized opportunities, sustained AI impact is closely associated with transforming capabilities, including the continuous refinement of business models and processes. DC transforming is essential for securing the long-term BMI value capture pillar. Organizations that track value creation across leading indicators and lagging outcomes gain a more comprehensive understanding of AI's contribution. Cultures emphasizing experimentation, iterative improvement, and workforce development appear better equipped to institutionalize successful pilots, translating initial DC-enabled successes into lasting competitive advantage.

7. Conclusion

The transformative potential of AI technologies promises to disrupt conventional business models, introducing novel operational paradigms and service delivery mechanisms. However, a significant *AI productivity paradox* persists: while organizations are rapidly investing in AI to capture this value, these investments often yield minimal returns. This disconnect arises largely from strategic misalignment, organizational inertia, and the complexity of data ecosystems. Consequently, there is an urgent need for innovative strategic approaches that enable organizations not only to adopt technology, but to navigate dynamic market changes and secure sustainable value.

This paper addresses the challenge of maximizing AI value by exploring the strategic integration of BMI with DC. Through a systematic literature review and in-depth interviews with AI practitioners, this research advances the understanding that technology adoption alone is insufficient for success. Instead, we argue that the realization of AI value is a sociotechnical process relying on customer-centric innovation, adaptive leadership, a robust culture of collaboration, and strict strategic alignment. Our findings suggest that successful AI adoption emerges from the synergistic interplay between developing dynamic capabilities and iterative business model refinement. Efforts that cultivate these capabilities in parallel with business model transformation are significantly more likely to convert the potential of AI into tangible, sustainable performance. In contrast, a disconnect between capability development and business model alignment limits the strategic contribution of AI investments.

While this research offers a comprehensive conceptual framework for maximizing AI value, certain limitations define the scope of our contributions. The qualitative nature of the study, utilising semi-structured interviews with eleven respondents across three organizations, prioritized depth of contextual insight over broad statistical generalizability. Additionally, the systematic review was delimited to a focused synthesis of 23 key academic publications, potentially excluding grey literature.

Future research should aim to expand the generalizability of these findings by incorporating quantitative methodologies and a broader participant base across diverse industry sectors. Specifically, we recommend comparative studies between organizations that have successfully realized AI benefits and those that have not, to empirically isolate the specific contributions of integrating BMI with DC. Furthermore, subsequent studies should investigate transforming these theoretical findings into actionable managerial frameworks. Such tools would empower organizations to strategically execute AI initiatives, integrate AI into core operations, and ensure continuous alignment with long-term business objectives.

References

[1] Afuah, A., 2014. Business model innovation: concepts, analysis, and cases. routledge.

[2] Åström, J., Reim, W., Parida, V., 2022. Value creation and value capture for ai business model innovation: a three-phase process framework. Review of Managerial Science 16, 2111–2133.

[3] Babina, T., Fedyk, A., He, A., Hodson, J., 2024. Artificial intelligence, firm growth, and product innovation. Journal of Financial Economics 151, 103745. doi:10.1016/j.jfineco.2023.103745.

[4] Babu, M.M., Rahman, M., Alam, A., Dey, B.L., 2021. Exploring big data-driven innovation in the manufacturing sector: evidence from UK firms. Annals of Operations Research URL: https://link.springer.com/10.1007/s10479-021-04077-1, doi:10.1007/s10479-021-04077-1.

[5] Bowman, C., 2015. The role of technology in the creation and capture of value. Technology Analysis & Strategic Management 27, 237–248.

[6] Burström, T., Parida, V., Lahti, T., Wincent, J., 2021. Ai-enabled business-model innovation and transformation in industrial ecosystems: A framework, model and outline for further research. Journal of Business Research 127, 85–95. URL: http://dx.doi.org/10.1016/j.jbusres.2021.01.016, doi:10.1016/j.jbusres.2021.01.016.

[7] Burström, T., Parida, V., Lahti, T., Wincent, J., 2021. Ai-enabled business-model innovation and transformation in industrial ecosystems: A framework, model and outline for further research. Journal of Business Research 127, 85–95.

[8] Côrte-Real, N., Oliveira, T., Ruivo, P., 2017. Assessing business value of big data analytics in european firms. Journal of Business Research 70, 379–390. URL: http://dx.doi.org/10.1016/j.jbusres.2016.08.011, doi:10.1016/j.jbusres.2016.08.011.

[9] Dubois, A., Gadde, L.E., 2014. "systematic combining"—a decade later. Journal of Business Research 67, 1277–1284.

[10] Eisenhardt, K.M., Martin, J.A., 2000. Dynamic capabilities: what are they? Strategic management journal 21, 1105–1121.

[11] Enholm, I.M., Papagiannidis, E., Mikalef, P., Krogstie, J., 2021. Artificial intelligence and business value: a literature review. Information Systems Frontiers 24, 1709–1734. URL: http://dx.doi.org/10.1007/s10796-021-10186-w, doi:10.1007/s10796-021-10186-w.

[12] Fink, A., 2003. The survey handbook. sage.

[13] Fountaine, T., McCarthy, B., Saleh, T., 2019. Building the ai-powered organization. Harvard Business Review 97, 62–73.

[14] Gao, Y., Liu, S., Yang, L., 2025. Artificial intelligence and innovation capability: A dynamic capabilities perspective. International Review of Economics and Finance 98, 103923. doi:10.1016/j.iref.2025.103923.

[15] Gupta, S., Modgil, S., Bhattacharyya, S., Bose, I., 2022. Artificial intelligence for decision support systems in the field of operations research: review and future scope of research. Annals of Operations Research 308, 215–274.

[16] Haefner, N., Wincent, J., Parida, V., Gassmann, O., 2021. Artificial intelligence and innovation management: A review, framework, and research agenda. Technological Forecasting and Social Change 162, 120392. doi:10.1016/j.techfore.2020.120392.

[17] Johnson, G., Whittington, R., Regnér, P., Angwin, D., Scholes, K., 2020. Exploring strategy. Pearson UK.

[18] Kelly, L.M., Cordeiro, M., 2020. Three principles of pragmatism for research on organizational processes. Methodological innovations 13, 2059799120937242.

[19] Knott, E., Rao, A.H., Summers, K., Teeger, C., 2022. Interviews in the social sciences. Nature Reviews Methods Primers 2. URL: http://dx.doi.org/10.1038/s43586-022-00150-6, doi:10.1038/s43586-022-00150-6.

[20] Kvale, S., Brinkmann, S., 2009. Interviews: Learning the craft of qualitative research interviewing. sage.

[21] Mikalef, P., Krogstie, J., Pappas, I.O., Pavlou, P., 2020. Exploring the relationship between big data analytics capability and competitive performance: The mediating roles of dynamic and operational capabilities. Information & Management 57, 103169.

[22] Opresnik, D., Taisch, M., 2015. The value of big data in servitization. International journal of production economics 165, 174–184.

[23] Osterwalder, A., Pigneur, Y., Tucci, C.L., 2005. Clarifying business models: Origins, present, and future of the concept. Communications of the Association for Information Systems 16. URL: http://dx.doi.org/10.17705/1CAIS.01601, doi:10.17705/1cais.01601.

[24] Page, M.J., McKenzie, J.E., Bossuyt, P.M., Boutron, I., Hoffmann, T.C., Mulrow, C.D., Shamseer, L., Tetzlaff, J.M., Akl, E.A., Brennan, S.E., et al., 2021. The prisma 2020 statement: an updated guideline for reporting systematic reviews. International journal of surgery 88, 105906.

[25] Pollock, A., Berge, E., 2017. How to do a systematic review. International Journal of Stroke 13, 138–156. URL: http://dx.doi.org/10.1177/1747493017743796, doi:10.1177/1747493017743796.

[26] Presti, C., De Santis, F., Bernini, F., 2023. Value co-creation via machine learning from a configuration theory perspective. European Journal of Innovation Management 26, 449–477.

[27] Ritala, P., Agouridas, V., Assimakopoulos, D., Gies, O., 2013. Value creation and capture mechanisms in innovation ecosystems: a comparative case study. International Journal of Technology Management 63, 244. URL: http://dx.doi.org/10.1504/IJTM.2013.056900, doi:10.1504/ijtm.2013.056900.

[28] Sadeghi, S., Amiri, M., 2022. Artificial intelligence and its application in optimization under. Data Mining: Concepts and Applications , 113.

[29] Sena, V., Nocker, M., et al., 2021. Ai and business models: The good, the bad and the ugly. Foundations and Trends® in Technology, Information and Operations Management 14, 324–397.

[30] Shollo, A., Hopf, K., Thiess, T., Müller, O., 2022. Shifting ml value creation mechanisms: A process model of ml value creation. The Journal of Strategic Information Systems 31, 101734.

[31] Sirmon, D.G., Gove, S., Hitt, M.A., 2008. Resource management in dyadic competitive rivalry: The effects of resource bundling and deployment. Academy of Management Journal 51, 919–935. URL: http://dx.doi.org/10.5465/amj.2008.34789656, doi:10.5465/amj.2008.34789656.

[32] Sjödin, D., Parida, V., Jovanovic, M., Visnjic, I., 2020. Value creation and value capture alignment in business model innovation: A process view on outcome-based business models. Journal of Product Innovation Management 37, 158–183.

[33] Storey, V.C., Yue, W.T., Zhao, J.L., Lukyanenko, R., 2025. Generative artificial intelligence: Evolving technology, growing societal impact, and opportunities for information systems research. Information Systems Frontiers URL: http://dx.doi.org/10.1007/s10796-025-10581-7,

doi:10.1007/s10796-025-10581-7.

[34] Teece, D.J., 2010. Business models, business strategy and innovation. Long Range Planning 43, 172–194. URL: http://dx.doi.org/10.1016/j.lrp.2009.07.003, doi:10.1016/j.lrp.2009.07.003.

[35] Teece, D.J., 2018. Business models and dynamic capabilities. Long Range Planning 51, 40–49. URL: http://dx.doi.org/10.1016/j.lrp.2017.06.007, doi:10.1016/j.lrp.2017.06.007.

[36] Teece, D.J., Pisano, G., Shuen, A., 1997. Dynamic capabilities and strategic management. Strategic management journal 18, 509–533.

[37] Verdin, P., Tackx, K., et al., 2015. Are you creating or capturing value? a dynamic framework for sustainable strategy. M-RCBG Working Paper Series 36, 1–19.

[38] Verdin, P.J., Tackx, K., 2015. Are you creating or capturing value? a dynamic framework for sustainable strategy. URL: https://api.semanticscholar.org/CorpusID:109740325.

[39] Vidgen, R., Shaw, S., Grant, D.B., 2017. Management challenges in creating value from business analytics. European Journal of Operational Research 261, 626–639.

[40] Wilson, C., 2014. Semi-Structured Interviews. Elsevier. p. 23–41. URL: http://dx.doi.org/10.1016/B978-0-12-410393-1.00002-8, doi:10.1016/b978-0-12-410393-1.00002-8.

[41] Zhang, H., Wang, W., Gupta, S., 2023. How do firms capture value in a full-scene smart service? effectiveness of value proposition and co-creation capabilities. Industrial Marketing Management 112, 128–144.