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STRATEGIC ALIGNMENT OF ARTIFICIAL INTELLIGENCE CAPABILITIES WITH BUSINESS STRATEGY AND VALUE CREATION: A SYSTEMATIC LITERATURE REVIEW FROM AN INFORMATION SYSTEMS PERSPECTIVE

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Artificial intelligence (AI) is increasingly positioned as a strategic resource, yet its contribution to sustained competitive advantage remains uneven and theoretically fragmented. This study addresses this gap by conducting a systematic literature review (SLR) of 79 studies at the intersection of AI, information systems, and business strategy. Adopting a concept-centric and theory-building approach, the review synthesizes prior research to identify key mechanisms, inconsistencies, and boundary conditions shaping AI-enabled strategic outcomes. The findings reveal that AI does not create value as a standalone technological capability, but as part of a broader socio-technical system requiring alignment between digital capabilities, organizational processes, governance structures, and culture. Six interrelated themes are identified, encompassing technological foundations, value creation, task augmentation, decision support, leadership, and organizational integration. Cross-study analysis highlights persistent tensions—such as automation versus human judgment and efficiency versus strategic flexibility—that condition the realization of AI-driven value. Building on these insights, the study develops an integrative conceptual model that reconceptualizes strategic alignment as a dynamic, capability-driven, and tension-laden process. The model positions AI/IT capabilities as microfoundations that enable sensing, seizing, and reconfiguring, while emphasizing the mediating role of organizational culture and the importance of strategic orchestration. The study contributes to Information Systems and strategic management literature by advancing a configurational perspective on AI-enabled value creation, extending strategic alignment theory toward a dynamic and paradox-oriented view, and refining the microfoundations of dynamic capabilities in the context of AI. The findings also provide actionable guidance for organizations seeking to translate AI investments into sustained strategic value.

Keywords: Artificial Intelligence; Information Systems; Machine Learning; Digital Transformation; Corporate Strategy; Innovation.

INTRODUCTION

Artificial intelligence (AI) has emerged as a transformative force reshaping business strategy across industries (Davenport & Ronanki, 2018; Malik, 2025; Rai et al., 2021). Once a speculative frontier, AI is now a central driver of digital transformation and competitive advantage, enabling improved decision-making, operational efficiency, and new value creation. Technologies such as machine learning, natural language processing, robotics, and advanced analytics allow firms to process large-scale data, automate complex tasks, and generate actionable insights (Ransbotham et al., 2020). Beyond efficiency gains, AI increasingly shapes competitive dynamics through predictive strategy, personalization, and business model innovation (Brynjolfsson & McAfee, 2014; Górka et al., 2025; Gottumukkala & Prasad, 2025).

Despite growing attention, research on AI and business strategy remains fragmented across

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Information Systems (IS), strategic management, economics, and computer science. This dispersion has produced inconsistent conceptualizations of AI's strategic role and limited theoretical convergence (Margherita, 2021; Schuetz & Venkatesh, 2020; Yuxuan et al., 2025). Much of the literature relies on sector-specific or descriptive studies that examine isolated applications without embedding them in broader strategic frameworks (Tambe et al., 2019). Consequently, understanding of how AI contributes to sustained competitive advantage—and under what conditions—remains limited.

Existing systematic literature reviews (SLRs) and bibliometric studies also remain constrained in scope and explanatory depth. Most focus on specific domains—such as AI adoption, analytics capabilities, or digital transformation—while treating AI primarily as a technological enabler rather than a strategically embedded capability. As a result, they offer limited insight into the mechanisms linking AI capabilities to strategic outcomes. Moreover, IS and strategic management perspectives are rarely integrated, limiting theoretical convergence and explanation of long-term competitive advantage (Koulis et al., 2025).

From an IS perspective, AI is better understood as a strategic organizational resource embedded in processes, capabilities, and decision structures (Rai et al., 2021). It supports activities such as customer analytics, predictive modelling, process automation, and business model innovation (Schuetz & Venkatesh, 2020). Its value depends less on adoption and more on integration within organizational capabilities and governance. This shift also reshapes leadership and decision-making, requiring data-driven reasoning, analytical expertise, ethical oversight, and effective human–AI collaboration (Fascinari & English, 2025; Ghosh et al., 2023; Kaushik, 2022; Kitsios & Kamariotou, 2021).

SLRs are essential for consolidating fragmented knowledge, identifying gaps, and advancing theory through structured synthesis (Snyder, 2019). Unlike narrative reviews, they provide transparent and replicable methods that support cumulative knowledge development (Tranfield et al., 2003). When theory-driven, SLRs enable conceptual refinement, cross-study comparison, and framework development (Webster & Watson, 2002).

Building on this need, this study conducts a theory-driven SLR at the intersection of AI and business strategy, integrating fragmented research through the lens of Dynamic Capabilities. It conceptualizes AI as a bundle of organizational capabilities enabling sensing, seizing, and transforming activities. Through systematic cross-study comparison, the review identifies converging and diverging patterns and explicates the mechanisms linking AI capabilities to strategic outcomes, moving beyond descriptive synthesis toward an explanatory framework of AI-enabled competitive advantage.

This study makes three contributions. First, it provides a structured cross-study synthesis that reveals patterns, divergences, and key tensions in how AI is conceptualized in business strategy research. Second, it advances theory by clarifying the mechanisms through which AI capabilities enable dynamic capabilities and strategic alignment, offering a more precise explanation of AI-driven competitive advantage. Third, it develops a conceptual framework that extends existing theory by incorporating organizational contingencies – such as culture, governance, and capability orchestration-providing a more nuanced understanding of AI-enabled transformation.

The remainder of the paper is structured as follows. Section 2 presents the theoretical background. Section 3 outlines the methodology and research design. Section 4 presents the classification framework and results. Section 5 develops the conceptual model grounded in dynamic capabilities theory. Section 6 concludes with discussion and future research directions.

THEORETICAL BACKGROUND OF ARTIFICIAL INTELLIGENCE

Evolution of Artificial Intelligence

Artificial intelligence (AI) has evolved from a symbolic reasoning paradigm into a data-driven, learning-based discipline (Copeland, 2015; Goodfellow et al., 2016). Early conceptualisations, grounded in Turing's behavioural definition of intelligence, framed AI as the simulation of human reasoning through formal logic (Turing, 1950). While influential, this approach proved limited in addressing uncertainty and real-world complexity, as reflected in the constrained applicability of expert systems (Buchanan & Shortliffe, 1984).

The emergence of machine learning marked a shift from rule-based reasoning to statistical inference, enabling systems to learn patterns from data rather than rely on explicitly encoded knowledge (Bishop, 2006; Rumelhart et al., 1986). This transition was further accelerated by deep learning, which introduced hierarchical representation learning and significantly improved performance in domains such as perception and natural language processing (Goodfellow et al., 2016; LeCun et al., 2015).

Contemporary AI is therefore best understood as a layered system of interdependent subfields, shaped by the interaction of algorithms, data availability, and computational infrastructure (Chui et al., 2023; Jurafsky & Martin, 2020; Litjens et al., 2017). Importantly, this evolution transforms AI from a static tool into a dynamic, learning-oriented capability, necessitating theoretical perspectives that can explain adaptation, reconfiguration, and continuous value creation.

Artificial Intelligence in Organizations

AI adoption in organizations represents a socio-technical transformation rather than a purely technological shift (Brynjolfsson & McAfee, 2014). Although AI is often associated with efficiency gains and improved decision-making, empirical evidence suggests that such benefits are conditional on organizational readiness, including data infrastructure, workforce capabilities, and process alignment (Bara, 2026; Bughin et al., 2017; Challapally et al., 2025; Stanford HAI, 2025).

A central tension in the literature concerns AI's dual role as both an automation tool and a catalyst for organizational change. Its implementation reshapes decision authority, task allocation, and collaboration patterns, requiring adjustments in leadership practices and employee roles (Murire, 2024). Thus, AI value is mediated by human factors such as trust, skills, and acceptance, with misalignment often leading to resistance and diminished returns (Zhao et al., 2025).

Despite substantial investment, many firms struggle to achieve AI maturity due to structural barriers such as data silos, limited integration, and governance gaps (Bughin et al., 2017; Challapally et al., 2025). Ethical concerns—including bias, transparency, and accountability also complicate adoption, highlighting the importance of explainability and human–AI collaboration (Bello et al., 2025; Voigt & von dem Bussche, 2017).

Overall, the literature indicates that AI creates value only when embedded within organizational systems and aligned with processes, capabilities, and governance structures (Bara, 2026; Gottumukkala & Prasad, 2025; Hu et al., 2025; Jia & Liu, 2025; Machucho & Ortiz, 2025). This underscores that value creation depends on the ability to integrate and reconfigure technological and human resources over time, reinforcing the relevance of a dynamic, capability-based perspective.

Strategic Use of Information Technology in Organizations

The strategic value of AI can be understood through the Information Systems (IS) perspective, which emphasizes the interaction between technological capabilities and organizational context (Misra et al., 2024). While IT refers to infrastructure, IS encompasses the socio-technical systems through which information is generated and used (Bakopoulos & Treacy, 1985). This distinction highlights that technological assets alone do not generate value without organizational integration.

The Strategic Alignment Model suggests that competitive advantage depends on the alignment between business strategy, IT strategy, and organizational infrastructure (Henderson & Venkatraman, 1993). Similarly, the resource-based view posits that IT and AI create value only when embedded in firm-specific resources and complemented by organizational routines and data assets (Keen, 1981).

However, these perspectives are limited in explaining how value is sustained in dynamic environments. Dynamic capabilities theory extends this view by focusing on how organizations integrate, build, and reconfigure resources over time. This is particularly relevant for AI, where value depends on continuous learning, adaptation, and alignment rather than one-time implementation (Davenport, 2018).

Figure 1 synthesizes these perspectives by conceptualising AI as a dynamic capability emerging from the alignment of IT infrastructure, data resources, and organizational processes. It provides a theoretical bridge between IS research and the dynamic capabilities lens adopted in this study.

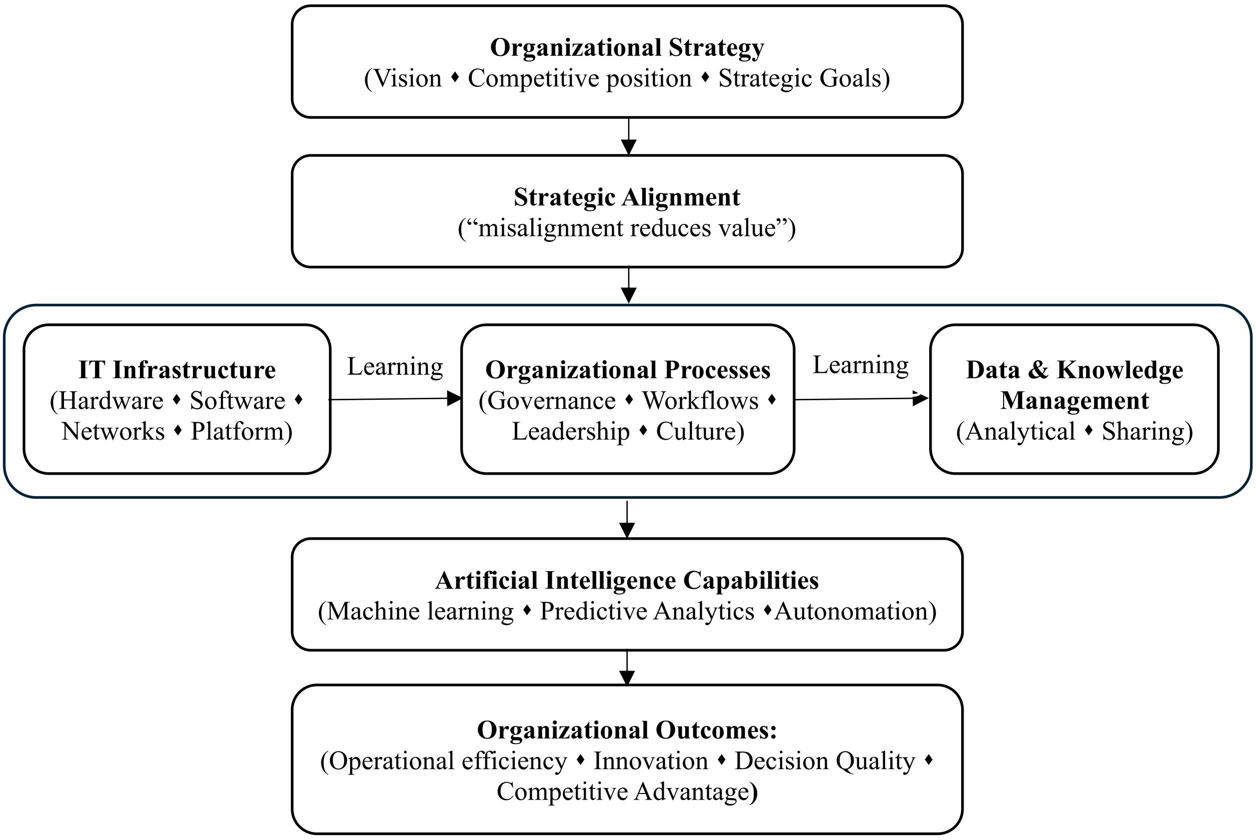

Figure 1: Conceptual foundation of AI-enabled strategic alignment.
AI capabilities emerge from the alignment of IT infrastructure, data resources, and organizational processes, enabling the translation of technological inputs into organizational value.

As illustrated, misalignment constrains value creation, reinforcing that AI should be understood not as an incremental extension of IT but as a capability requiring continuous orchestration. Despite the relevance of these perspectives, prior research—including existing SLRs—has rarely integrated them into a unified explanatory framework, instead emphasizing descriptive or domain-specific insights.

In sum, the strategic impact of AI depends on its alignment with organizational systems and its integration with complementary resources. However, existing research lacks a coherent explanation of how such alignment is achieved and sustained. Addressing this gap requires a dynamic, capability-based perspective, which provides the foundation for the systematic literature review conducted in this study.

RESEARCH OBJECTIVES

Information technology has long been recognized as a key driver of organizational transformation and competitive advantage (Bakopoulos & Treacy, 1985; Barney, 1991; Teece et al., 2007). The emergence of artificial intelligence (AI), however, introduces new strategic complexity in how digital technologies are embedded within business strategy (Borges et al., 2020; Kitsios & Kamariotou, 2021; Shinkle, 2024). Unlike traditional IT, AI enables pattern recognition, predictive analytics, and cognitive-like decision support, thereby extending automation and enhancing data-driven decision-making capabilities (Baig et al., 2024; Chui et al., 2023; Davenport, 2018; Tallam, 2025).

Despite these capabilities, organizations continue to face significant challenges in translating AI investments into sustained strategic value. Common barriers include difficulties in demonstrating return on investment, misalignment between AI initiatives and strategic priorities, and tensions between short-term operational efficiency and long-term strategic transformation (Malik, 2025; Murire, 2024). Although adoption is accelerating, enterprise-wide integration remains limited, indicating persistent challenges related to alignment, scalability, and value realization (Akerman, 2025; Gartner, 2025; Singla et al., 2025). In addition, AI introduces broader strategic and organizational implications, including workforce transformation, regulatory and ethical concerns, industry disruption, and risks of technological obsolescence (Elsayed, 2025). These challenges highlight the importance of governance, strategic alignment, and capability orchestration for effective AI deployment (OECD, 2025).

Against this backdrop, this study conducts a systematic literature review (SLR) on the integration of AI into business strategy, with a focus on the Information Systems (IS) perspective. It synthesizes and critically evaluates existing research to develop a conceptual framework that identifies key drivers, mechanisms, and outcomes of AI-enabled strategic transformation. In doing so, the study contributes to cumulative knowledge development by structuring fragmented insights and providing a foundation for future research and practice (Collins et al., 2021).

Research Questions

To achieve these objectives, the study addresses the following research questions:

RQ1: What factors influence the strategic adoption and integration of artificial intelligence within organizations?

RQ2: What strategic outcomes and value implications arise from the integration of AI into business strategy?

RQ3: What key themes, research gaps, and future research directions emerge from the literature on AI and business strategy?

Research Methodology

This study employs a SLR combined with a concept-centric analytical approach to examine the strategic integration of AI within organizations. SLRs provide a rigorous, transparent, and replicable method for synthesizing dispersed knowledge and are particularly suited to theory development in emerging and interdisciplinary domains (Kitchenham et al., 2009; Tranfield et al., 2003). Beyond aggregating prior findings, SLRs can support theory building by identifying patterns, relationships, and underlying mechanisms across studies when guided by a clear conceptual lens (Snyder, 2019).

Consistent with concept-centric approaches in Information Systems research, this review organizes the literature around key constructs rather than authors or chronology (Webster & Watson, 2002). This enables analytical synthesis by systematically comparing how concepts such as AI capabilities, strategic alignment, and value creation are defined and related across studies. In contrast to purely descriptive reviews, this approach facilitates the identification of causal mechanisms and conceptual gaps, thereby supporting the development of an integrative framework of AI-enabled strategic transformation.

Theoretical Positioning

The review adopts a theory-building perspective grounded in Information Systems literature synthesis. Rather than testing predefined hypotheses, it follows an inductive logic, deriving insights from patterns across studies. This aligns with established SLR guidance emphasizing theory development through knowledge consolidation, construct refinement, and relationship building (Snyder, 2019).

AI is conceptualized as a strategic organizational capability interacting with IS infrastructure, managerial decision-making, and competitive strategy. Through concept-driven synthesis, the review identifies mechanisms linking AI capabilities to strategic alignment and value creation, extending existing perspectives by positioning AI as a dynamic and evolving capability.

Conceptual Scope

The review focuses on core constructs of AI-enabled strategy, including artificial intelligence, generative AI, machine learning, deep learning, IS strategy, business strategy, strategic alignment, and competitive advantage. These define the conceptual scope and guide study selection. Recent advances in generative AI and large language models further enhance strategic relevance by enabling scalable knowledge generation and decision support (Chui et al., 2023).

Literature Search Strategy and Study Selection

The literature search followed established SLR protocols to ensure transparency and reproducibility (Tranfield et al., 2003). Multiple academic and practitioner-oriented databases were used, including Google Scholar, Web of Science, ScienceDirect, EBSCOhost, ABI/INFORM (ProQuest), MIT Sloan Management Review, and McKinsey Global Institute. Search strings combined key terms such as "artificial intelligence," "machine learning," "generative AI," and "strategic information technology" using Boolean operators. The search was conducted between June 2025 and February 2026.

Study selection followed a structured multi-stage process—identification, screening, eligibility, and inclusion—guided by conceptual relevance, theoretical contribution, and methodological rigor (Gough et al., 2013). Backward and forward citation tracking enhanced coverage and reduced omission risk. From 1,688 initial publications, 79 studies were retained for final analysis (Figure 2).

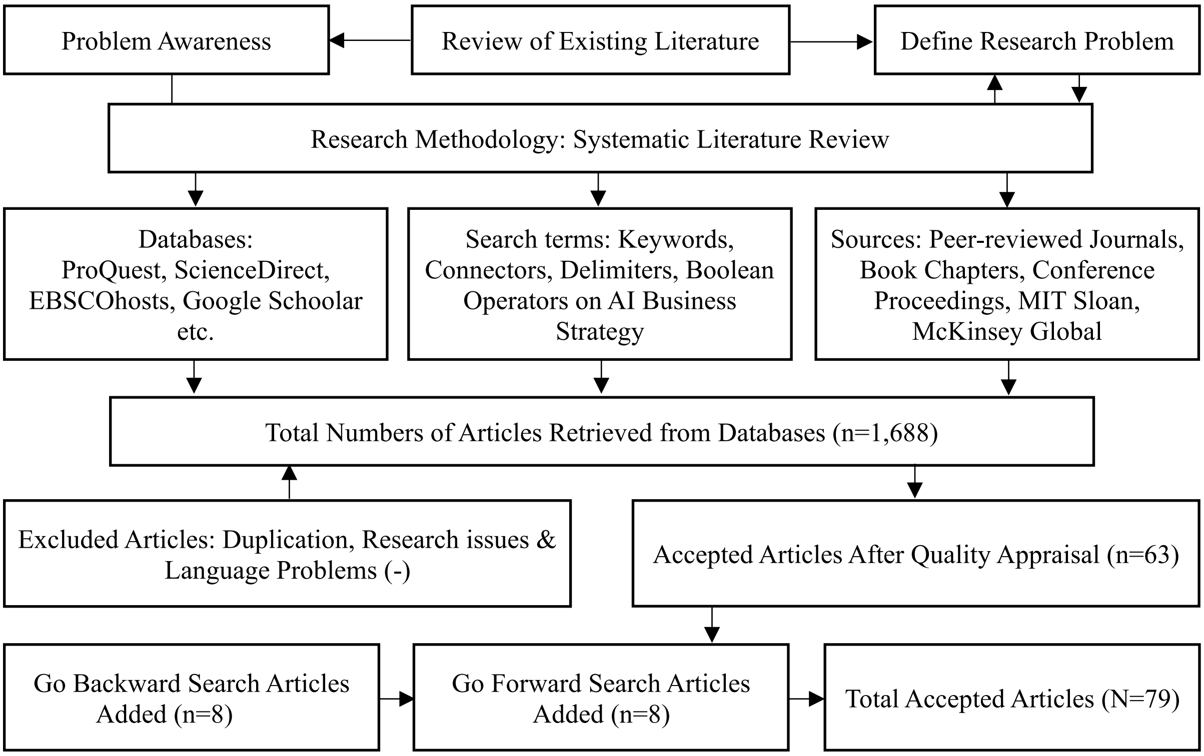

Figure 2: Study selection process for the systematic literature review (SLR)
Figure illustrates the stages of identification, screening, eligibility assessment, and final inclusion of studies in the SLR following established SLR protocols for transparency, rigor, and reproducibility.

These procedures ensure transparency and reproducibility while providing a robust foundation for conceptual synthesis rather than a purely descriptive review.

Data Extraction and Conceptual Synthesis

Data extraction focused on capturing not only descriptive attributes (e.g., methods, contexts) but also underlying theoretical constructs, relationships, and mechanisms (Ikart, 2019). Using a concept-centric approach, studies were coded and grouped according to core constructs, enabling the identification of recurring themes, convergences, and inconsistencies (Wabster & Watson, 2002).

The synthesis process was explicitly analytical rather than procedural. It involved iteratively comparing constructs across studies, identifying patterns of alignment and divergence, and abstracting higher-level relationships. This process supports theory building by moving from fragmented empirical insights toward an integrated conceptual framework linking AI capabilities, strategic alignment, and organizational outcomes.

Validity and Study Limitations

The validity of the review is assessed in line with established SLR quality criteria, particularly transparency, rigor, and reproducibility (Kitchenham et al., 2009; Tranfield et al., 2003).

– Construct validity was strengthened through clearly defined conceptual boundaries and a theory-informed coding scheme aligned with IS literature.
– Internal validity was enhanced through iterative coding, cross-checking, and collaborative synthesis, reducing subjective bias in interpretation.
– External validity was supported by the inclusion of diverse sources across disciplines, industries,

and publication types, improving the generalizability of insights.
- Conclusion validity was ensured through systematic comparison of findings and transparent documentation of the synthesis process.

Despite these measures, limitations remain. The review may be subject to publication bias, as peer-reviewed studies tend to report more developed findings. Additionally, concept-centric synthesis involves interpretive judgment, and trade-offs between breadth and depth may have led to the exclusion of some relevant studies (Ikart, 2019). Finally, given the rapid evolution of AI, findings should be interpreted within a dynamic technological and regulatory context.

Previous Literature Reviews and Alignment with Research Questions

To situate this study within existing knowledge and justify its research focus, this section synthesizes prior systematic literature reviews (SLRs) on artificial intelligence (AI) and business strategy. Rather than treating these studies as isolated contributions, the analysis adopts a concept-centric perspective to identify how AI has been conceptualized across prior reviews, what dimensions have been emphasized, and where theoretical integration remains limited. This synthesis is used to establish the need for a theory-building SLR that moves beyond descriptive aggregation toward mechanism-based explanation.

Overview of Prior Systematic Literature Reviews

Four influential SLRs published between 2020 and 2023 form the basis of this analysis. These studies were selected based on methodological rigor, disciplinary relevance to IS, and explicit engagement with AI-enabled strategic outcomes. As summarized in Table 1, prior reviews vary in scope but collectively provide fragmented insights into AI in business strategy.

Table 1: Summary of Previous Systematic Literature Reviews on AI and Business Strategy

Authors	Year	Methodology	Key Findings
Borges et al.	2020	SLR of peer-reviewed journals and conference proceedings across two databases using keywords including AI, business strategy, ML, and IT strategy	Identified four value perspectives: AI-enabled decision-making, automation, customer and employee engagement, and innovation
Kitsios & Kamariotou	2021	SLR of journals, conference proceedings, and book chapters across multiple databases using keywords such as AI, ML, DL, business strategy, and competitive strategy	Identified themes related to AI–strategy alignment, decision-making, and service innovation
Govori & Sejdija	2023	SLR focusing on AI adoption in SMEs across multiple databases	Identified cost, technical complexity, and skills shortages as major barriers to AI adoption in SMEs
Perifanis & Kitsios	2023	SLR of journals, conference proceedings, and book chapters across multiple databases using keywords including AI capability, business strategy, and digital transformation	Emphasized AI ambidexterity, capability orchestration, and governance

Across these studies, three dominant analytical orientations emerge: (i) AI adoption and enabling conditions (e.g., infrastructure, skills, costs), (ii) AI-enabled organizational capabilities (e.g., automation, decision-making, innovation), and (iii) governance and strategic alignment mechanisms (e.g., orchestration, ambidexterity, control structures). While these dimensions are widely acknowledged, they are typically examined in isolation rather than as interdependent elements of a unified strategic system.

This reveals a key limitation of existing SLRs: they primarily function as descriptive synthesis studies, focusing on categorization and thematic mapping rather than explanation of underlying mechanisms. As a result, prior reviews identify what is present in the literature but provide limited insight into how AI capabilities are developed, integrated, and translated into sustained strategic value.

- **Alignment with Research Question 1 (RQ1)**
  RQ1 examines the factors influencing the strategic adoption of AI within organizations. Prior SLRs identify multiple determinants, including technological readiness, financial constraints, and human capital limitations (Govori & Sejdija, 2023), as well as enabling

conditions such as governance structures and capability orchestration (Perifanis & Kitsios, 2023). Synthesizing these findings suggests that AI adoption is not driven by isolated factors but by the interaction of three interdependent dimensions: organizational readiness (skills, culture, resources), technological capability (data, infrastructure, algorithms), and governance and alignment mechanisms (strategy, coordination, control). However, existing SLRs tend to treat these dimensions separately, limiting explanatory depth and leaving the interdependencies between them under-theorized. This study addresses RQ1 by conceptualizing AI adoption as a capability- and alignment-dependent process, where adoption outcomes emerge from the interaction of organizational, technological, and governance systems rather than from discrete enabling or inhibiting factors.

– **Alignment with Research Question 2 (RQ2)**
RQ2 focuses on the strategic implications and value outcomes of AI integration. Prior SLRs consistently report benefits such as improved decision-making, automation, innovation, and enhanced customer engagement. However, these outcomes are predominantly framed at an operational level, with limited attention to how they translate into sustained competitive advantage. Cross-study synthesis indicates that AI value creation unfolds through a multi-stage process involving capability development, operational embedding, strategic alignment, and value scaling over time. While prior SLRs identify individual stages, they do not connect them into an integrated value realization pathway, nor do they account for temporal dynamics such as scaling challenges or alignment drift. This study addresses RQ2 by integrating fragmented insights into a value realization framework that links AI capability development to strategic alignment and long-term competitive advantage.

– **Alignment with Research Question 3 (RQ3)**
RQ3 explores key themes, gaps, and future research directions in AI and business strategy literature. Prior SLRs converge on several recurring themes, including AI-enabled decision-making, automation, innovation, and governance. At a higher level, these map onto three broader domains: capability development, strategic alignment, and governance and human–AI interaction. Despite this thematic convergence, the literature remains theoretically fragmented. Prior reviews draw on diverse and often disconnected perspectives, resulting in limited cumulative theory development. A key gap is the absence of an integrative framework that connects AI capabilities, governance mechanisms, and strategic outcomes within a unified explanatory model. Moreover, important tensions remain underexplored, including those between automation and human augmentation, innovation and control, and efficiency and adaptability. These unresolved tensions highlight the need for more integrative and mechanism-based theorization. This study addresses RQ3 by consolidating these fragmented themes and proposing a unified conceptual framework that integrates capability, governance, and strategic alignment perspectives.

– **Summary and Contribution Relative to Research Questions**
In summary, prior SLRs provide valuable but structurally fragmented insights into AI in business strategy. While they identify relevant factors (RQ1), outcomes (RQ2), and thematic areas (RQ3), they predominantly rely on descriptive synthesis and do not explain how these elements interact within a coherent strategic system. This limitation is both conceptual and methodological. Prior SLRs emphasize categorization and thematic mapping rather than concept-centric, mechanism-based explanation. Consequently, the literature lacks a unified theoretical account of how AI capabilities are developed, embedded, and leveraged for sustained competitive advantage. Addressing this gap, this study adopts a theory-building, concept-centric SLR approach that integrates fragmented insights into a mechanism-based framework linking AI-enabled capabilities, strategic alignment processes, and value creation outcomes. In doing so, it advances a more cumulative and theoretically coherent understanding of AI's role in business strategy and provides a foundation for future empirical and conceptual research.

CLASSIFICATION FRAMEWORK FOR CONCEPT ANALYSIS

Building on the prior SLR synthesis (Section 3.6), this section develops a concept-centric classification framework following Webster and Watson (2002). Rather than organizing studies thematically in isolation, the framework reconstructs the literature through comparative and configurational analysis, making explicit where findings converge, diverge, and under what conditions they hold. This shifts the review from narrative aggregation toward analytically integrated synthesis.

A total of 79 articles were retained following screening and quality appraisal. These studies were coded using a combined inductive–deductive approach aligned with RQ1–RQ3. Importantly, themes are not treated as discrete categories but as interdependent components of a socio-technical system, consistent with a dynamic capabilities perspective (Teece et al., 2007). This enables identification of mechanisms (how AI creates effects), tensions (why findings diverge), and boundary conditions (when outcomes differ). Articles were coded across multiple themes to reflect the overlapping and multi-level nature of AI-enabled transformation (Davenport & Ronanki, 2018; Jarrahi, 2018).

Six analytically derived themes structure the synthesis:
1. AI, ML, DL, and NLP;
2. Competitive Advantage, Innovation, and Value Creation;
3. AI and IT Capabilities: Task Augmentation;
4. Automation and Decision Support Systems;
5. Leadership and Strategic Decision-Making;
6. Organizational Culture and AI–IT Integration.

Rather than mapping one-to-one onto research questions, these themes collectively explain three interrelated processes: capability formation (RQ1), value realization (RQ2), and strategic alignment (RQ3). The analysis emphasizes cross-study comparison, contradictions, and generative mechanisms.

Results of the Concept Classification

AI, ML, DL, and NLP in Organizations

Across studies, there is strong convergence that AI technologies expand organizational capabilities in prediction, classification, and knowledge extraction (Chui et al., 2023; Jordan & Mitchell, 2015; LeCun et al., 2015; Litjens et al., 2017). However, a central divergence concerns whether these technologies constitute a source of competitive differentiation or a commoditized input.

One stream positions advances in deep learning and large language models as drivers of strategic advantage (Chui et al., 2023; Singla et al., 2025), while another argues that increasing accessibility reduces their differentiating potential (Chui et al., 2023; Koulis et al., 2025). Cross-study comparison suggests that this divergence is conditional rather than contradictory.

The underlying mechanism linking AI to strategic outcomes is not technological sophistication alone, but its embedding within firm-specific data, processes, and governance structures (Chui et al., 2023; Koulis et al., 2025). Studies converge on the insight that AI creates value when combined with complementary assets, particularly proprietary data and organizational routines (Koulis et al., 2025; Singla et al., 2025).

This yields a clear boundary condition:
- Where AI is standardized, it contributes to operational parity.
- Where AI is deeply integrated, it enables differentiation.

Thus, AI is best understood as a context-dependent, system-level capability, rather than an independent resource (Chui et al., 2023; Koulis et al., 2026).

Competitive Advantage, Innovation, and Value Creation

The literature consistently links AI to improved decision-making, innovation, and efficiency (Barney, 1991; Teece et al., 2007). However, there is systematic divergence regarding the durability of AI-enabled competitive advantage.

Some studies emphasize sustained advantage through cumulative learning and capability reconfiguration (Barney, 1991; Teece et al., 2007), while others highlight rapid imitation and competitive convergence (Gartner, 2025; Singla et al., 2025). Cross-study synthesis indicates that these perspectives reflect different capability configurations rather than conflicting evidence.

The key mechanism is co-specialization of AI with organizational capabilities, particularly through unique data and embedded routines (Bach et al., 2025; Porter & Heppelmann, 2017). Sustained advantage emerges when firms continuously reconfigure these elements, whereas superficial adoption leads to temporary gains.

A second comparative pattern identifies two innovation pathways:
– Incremental innovation (efficiency and process optimization)
– Transformational innovation (new business models)

Both are widely observed (Christensen, 1997; Porter & Heppelmann, 2017; Singla et al., 2025), but transformational outcomes are associated with deeper integration and higher capability maturity (Bach et al., 2025; Jetha et al., 2025).

Overall, the literature converges on a conditional insight: AI contributes to competitive advantage through continuous orchestration of data, capabilities, and strategy, rather than adoption alone.

AI and IT Capabilities: Task Augmentation

A dominant perspective conceptualizes AI as augmenting human capabilities (OECD, 2025; World Economic Forum, 2026). However, empirical findings diverge significantly.

While many studies report productivity and decision-quality improvements, others identify risks such as skill degradation, overreliance, and workforce polarization (Bello et al., 2026; Lee & Chen, 2026). Cross-study comparison indicates that these outcomes reflect different configurations of human–AI interaction rather than contradictions.

The key mechanism is capability complementarity, where AI contributes analytical strength and humans provide contextual judgment (OECD, 2025). This complementarity depends on boundary conditions including task complexity, user expertise, and system transparency (Bara, 2026; Lee & Chen, 2026).

A consistent pattern emerges:
– In high-skill, well-governed contexts, augmentation dominates (World Economic Forum, 2026).
– In low-skill or weakly governed contexts, substitution or negative effects arise (Bello et al., 2026).

Thus, augmentation is not inherent but contingent on alignment between technology, skills, and organizational design.

Automation and Decision Support Systems

AI-enabled DSS are widely associated with improved decision speed and analytical depth (Arnott & Pervan, 2014; Chui et al., 2023; Tallam, 2025). However, the literature reveals a persistent tension between efficiency and control.

Some studies emphasize accuracy gains, while others highlight risks such as automation bias and reduced accountability (Lyytinen & Newman, 2008; Mosier et al., 1998). Cross-study synthesis shows that this divergence is mediated by governance mechanisms, particularly transparency, explainability, and accountability.

Where such mechanisms are strong, AI enhances decision-making; where they are weak, risks increase. Across studies, a consistent pattern is the emergence of hybrid decision architectures, combining AI-driven analysis with human oversight.

The underlying mechanism is distributed cognition, suggesting that strategic value lies not in full automation but in effective human–AI integration.

Leadership and Strategic Decision-Making

Leadership is consistently identified as critical but conceptualized differently across studies. Some emphasize visionary leadership (Davenport & Ronanki, 2018; Kraus et al., 2022), while others highlight governance and coordination roles (Bartsch et al., 2025; Hu et al., 2025).

Cross-study comparison suggests these differences reflect stages of AI maturity. Early stages prioritize vision and experimentation, whereas later stages require orchestration and governance.

A consistent finding is the emergence of hybrid decision authority, where AI supports but does not replace strategic judgment (Jetha et al., 2025; Lee & Chen, 2026). This indicates a shift toward augmented managerial cognition, requiring new competencies in data interpretation and ethical oversight (Davenport & Ronanki, 2018).

Organizational Culture and AI–IT Integration

Organizational culture is widely recognized but inconsistently positioned. Some studies treat it as a primary driver, while others see it as secondary (Bach et al., 2025; Mutale & El-Gayar, 2024).

Cross-study synthesis clarifies that culture functions primarily as a moderating condition, shaping whether AI initiatives scale or stall. Its impact is strongest in contexts of uncertainty, low trust, and high transformation intensity (World Economic Forum, 2026).

The key mechanism is alignment between cultural norms and technological change. Where alignment exists, adoption accelerates; where misalignment persists, resistance limits value realization (Bach et al., 2025). Thus, culture conditions outcomes rather than independently determining them.

Integrative Synthesis Across Themes

Across all six themes, similar constructs are associated with both positive and negative outcomes depending on context. AI capabilities enable both differentiation and commoditization; automation increases efficiency but may reduce control; augmentation enhances productivity but may create skill imbalances.

These are not contradictions but systematic tensions arising from the interaction of technological, organizational, and governance dimensions. The central analytical insight is that AI-enabled strategy is configurational and contingent. Outcomes depend on the alignment of:
– technological capabilities,
– organizational processes and skills,
– governance and leadership structures.

This leads to a refined theoretical contribution: AI should be conceptualized as a system-level dynamic capability, whose value emerges through alignment and orchestration rather than standalone deployment (Teece et al., 2007). This extends prior SLRs by explicitly identifying mechanisms, tensions, and boundary conditions, rather than aggregating factors.

Link to Research Questions and Conceptual Model

Table 2 synthesizes the mechanisms identified across themes and links them to RQ1–RQ3. Rather than serving as a descriptive summary, it makes explicit the comparative logic and configurational relationships underlying the framework, showing how capability formation, value realization, and alignment interact within an integrated system.

Table 2: Summary Classification of Concepts: Themes, Key Mechanisms, and Research Questions

Theme	Core Focus	Key Mechanisms	Primary RQ(s)
AI, ML, DL, NLP	Foundational technologies	Data processing and predictive expansion; embedding in processes and governance; role in dynamic capabilities	RQ1, RQ3
Competitive Advantage, Innovation, Value Creation	Strategic outcomes	Inimitable data–capability combinations; process and business model innovation; stakeholder-oriented value	RQ2, RQ3
Task Augmentation	Human–AI collaboration	Complementarity of AI and human judgment; productivity gains; dependence on trust and skills	RQ1, RQ2
Automation and DSS	Decision-making systems	AI-driven analytical augmentation; risks of bias and overreliance; hybrid decision architectures	RQ1, RQ2
Leadership	Strategic governance	Role of leadership in AI integration; importance of digital literacy; hybrid decision authority	RQ1, RQ3
Culture and AI–IT Integration	Organizational context	Learning-oriented culture; resistance and trust barriers; governance and change management	RQ1, RQ3

The classification framework demonstrates that existing AI–strategy research lacks explicit system-level integration. By systematically identifying convergences, divergences, and boundary conditions, this study moves beyond prior SLRs toward a mechanism-based and configurational understanding of AI-enabled strategy.

This provides the analytical foundation for the conceptual model in Section 5, which formalizes how tensions, complementarities, and boundary conditions jointly shape strategic outcomes.

CONCEPTUAL MODEL: AI/IT AND BUSINESS STRATEGY ALIGNMENT

Building on the thematic synthesis in Section 4, this study develops a conceptual model of AI/IT-enabled strategic alignment that explains how digital capabilities are transformed into strategic value through organizational and managerial mechanisms. The model integrates insights from Dynamic Capabilities and strategic alignment theory and is grounded in three interrelated clusters identified in the SLR: (1) digital capability foundations (Themes 1–4), (2) strategic orchestration mechanisms (Theme 5), and (3) organizational integration mechanisms (Theme 6).

Rather than conceptualizing alignment as a static fit, the model (Figure 3), advances a processual, capability-based view in which alignment emerges through continuous interaction between technological capabilities, managerial actions, and organizational context.

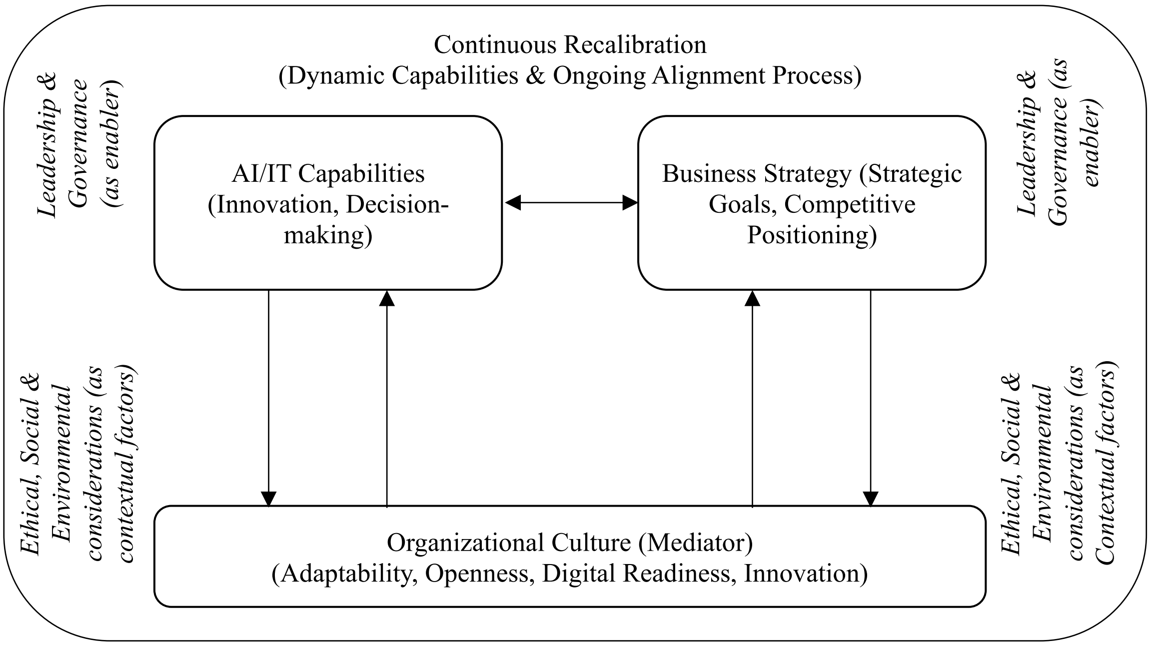

Figure 3: Conceptual Model of AI/IT-enabled business strategy alignment
Illustrating the relationships between digital capabilities, dynamic capability processes (sensing, seizing, reconfiguring), and organizational context in generating strategic value.

Conceptual Relationships and Theoretical Positioning

The framework (Figure 3) specifies three core relationships:
- AI/IT capabilities → dynamic capability processes (sensing, seizing, reconfiguring)
- Dynamic capability processes → strategic alignment outcomes
- Organizational culture → mediating and conditioning mechanism

AI/IT capabilities are positioned as microfoundations, dynamic capabilities as transformational mechanisms, and strategic alignment as the realized outcome. The model also incorporates structural tensions identified in the literature:
- Automation vs. human judgment (efficiency vs. control)
- Data-driven optimization vs. strategic flexibility (exploitation vs. exploration)
- Technological capability vs. organizational readiness (capability–context misalignment)

These tensions are not anomalies but conditions shaping how alignment is achieved.

Digital capability foundations capture the technological and operational bases through which organizations deploy AI, including AI infrastructure (Theme 1), analytics capabilities (Theme 2), decision support (Theme 3), and automation and augmentation (Theme 4). These capabilities expand information processing and decision support but do not directly generate strategic value. Instead, their impact depends on integration into higher-order organizational processes (Ackerman, 2025; Jordan & Mitchell, 2015; Koulis et al., 2025).

AI/IT Capabilities as Strategic Microfoundations

The literature consistently identifies AI technologies—such as machine learning, deep learning, and natural language processing—as foundational capabilities enabling large-scale data processing and predictive analysis (Koulis et al., 2025; LeCun et al., 2015). From a dynamic capabilities' perspective, these constitute microfoundations that underpin higher-order capabilities (Teece et al., 2007). Specifically, AI/IT capabilities enhance:

– **Sensing** through improved environmental scanning and pattern recognition
– **Seizing** through data-driven evaluation of strategic options
– **Reconfiguring** through process automation and organizational redesign

However, synthesis shows these microfoundations are necessary but insufficient. Without effective orchestration and integration, AI-generated insights may not translate into strategic action.

Strategic Alignment as a Dynamic Capability

This study reconceptualizes strategic alignment as a dynamic capability rather than a static fit (Henderson & Venkatraman, 1993; Teece et al., 2007). Alignment emerges through iterative cycles of:

– **Sensing**, enhanced by AI-driven analytics (Themes 1–2)
– **Seizing**, enabled by AI-supported decision systems (Theme 3)
– **Reconfiguring**, operationalized through automation and augmentation (Theme 4)

A key insight is the tension between alignment and adaptability. While alignment emphasizes coherence, dynamic environments require continuous reconfiguration. AI intensifies this tension by accelerating decision cycles and increasing reliance on data-driven logic.

However, strategic orchestration (Theme 5) resolves this tension by aligning AI capabilities with strategic objectives, positioning leadership as a central integrative mechanism.

Organizational Culture as a Mediating Mechanism

Organizational culture (Theme 6) acts as both a mediating and conditioning mechanism shaping how AI capabilities translate into strategic alignment. Cultures characterized by trust, learning, and experimentation facilitate the integration of AI into decision-making (Cameron & Quinn, 2011), whereas resistance, low trust, or ethical concerns inhibit adoption (Mutale & El-Gayar, 2024).

Culture also moderates key tensions in the model. It mitigates automation bias by encouraging critical engagement, supports human–AI collaboration, and enables organizational learning. As such, culture functions as a socio-technical integrator determining whether AI capabilities produce strategic value.

Mechanisms of AI-Enabled Strategic Value Creation

Synthesizing the six themes, the model identifies four interrelated mechanisms:

– **Capability-enabled sensing:** Digital foundations (Themes 1–2) enhance environmental scanning and predictive modelling (Teece et al., 2007).
– **Data-driven seizing:** AI-supported decision-making (Theme 3) enables evidence-based strategy and resource allocation (Davenport & Ronanki, 2018).
– **Operational reconfiguration:** Automation and augmentation (Theme 4) transform workflows and enable adaptation (Brynjolfsson & McAfee, 2014).
– **Contextual mediation and integration:** Organizational culture (Theme 6) shapes how these processes are embedded in routines and decision structures.

These mechanisms are coordinated through strategic orchestration (Theme 5), which aligns capabilities with objectives and manages trade-offs such as efficiency vs. flexibility and automation vs. control.

Implications for Research

The model contributes by integrating dynamic capabilities and strategic alignment through the lens of AI-enabled transformation. It suggests several research directions. First, empirical work should examine how AI reshapes the microfoundations of sensing and seizing in dynamic environments. Second, further research is needed on how leadership and governance influence capability orchestration. Third, studies should explore how human–AI collaboration affects decision quality and accountability. Finally, longitudinal research is needed to examine how culture and learning shape alignment over time.

Overall, the model positions AI–business strategy alignment as a dynamic, tension-filled, and socio-technical process. By linking AI/IT capabilities to dynamic capability processes and alignment outcomes, it provides a mechanism-based explanation of how organizations generate sustained value from AI.

DISCUSSION

Analytical Synthesis of the Literature

Rather than treating AI as a technological driver of performance, this review suggests a more fundamental reinterpretation: AI reshapes the logic through which strategic value is generated. Variation in outcomes is not explained by adoption alone, but by how AI is integrated into broader socio-technical systems.

This challenges a core assumption in Information Systems and strategy research—that technological capability can be treated as a stable input into performance. Instead, AI operates as a contingent and interaction-dependent capability whose value emerges only through alignment with organizational processes, governance structures, and cultural conditions.

More importantly, the findings show that AI alters the internal dynamics of Dynamic Capabilities. While prior research conceptualizes sensing, seizing, and reconfiguring as separable processes, AI compresses their temporal and functional boundaries. Sensing becomes continuous through real-time analytics, seizing becomes increasingly data-driven, and reconfiguring becomes faster but more constrained by data and system architectures. This creates tighter coupling across processes—enhancing responsiveness but also increasing systemic fragility.

At the same time, the literature reveals persistent structural tensions that cannot be resolved through optimization alone. The tension between automation and human judgment reflects a trade-off between efficiency and accountability, while the tension between data-driven optimization and strategic flexibility reflects an intensified exploitation–exploration dilemma. These patterns indicate that AI-enabled strategy is inherently paradoxical rather than linear. Organizations do not simply align AI with strategy; they must continuously manage competing demands within evolving configurations.

This perspective helps explain why similar AI investments produce divergent outcomes. Success depends less on capability possession than on the ability to orchestrate capabilities under conditions of tension. Accordingly, many reported "failures" of AI reflect breakdowns in alignment and integration rather than technological limitations. AI adoption should therefore be understood as a system-level transformation problem, not a technology implementation challenge.

Finally, the review highlights a critical gap: while AI is frequently associated with short-term efficiency gains, there is limited explanation of how these gains translate into sustained competitive advantage. This suggests that the central research question is not whether AI creates value, but under what conditions that value can be stabilized and scaled.

Theoretical Contributions

This study contributes to Information Systems and strategic management literature in five ways.

First, it reconceptualizes AI as a contingent, system-level capability rather than a discrete technological resource. Unlike traditional IT capabilities, AI is inherently dependent on data, learning, and continuous adaptation. Its value is therefore conditional on integration with organizational processes and governance, extending IS capability perspectives toward a configuration-based view of digital value creation.

Second, it advances strategic alignment theory by reframing alignment as a dynamic and tension-driven process. Traditional models emphasize a state of fit (Henderson & Venkatraman, 1993), whereas the findings show that AI intensifies environmental dynamism and introduces persistent trade-offs. Alignment is thus better understood as an ongoing capability of managing tensions rather than achieving equilibrium.

Third, the study refines dynamic capabilities theory by showing how AI reshapes its microfoundations. While the sensing–seizing–reconfiguring framework remains relevant (Teece et al., 2007), AI embeds these processes within data-driven systems, increasing their speed, interdependence, and path dependency. This suggests that AI-enabled capabilities are not simply extensions of existing dynamic capabilities but represent digitally mediated forms requiring further theoretical development.

Fourth, the study elevates organizational culture and governance from contextual factors to causal mechanisms. Rather than acting as background conditions, they actively determine whether AI capabilities are translated into strategic outcomes by shaping trust, adoption, and learning. This positions them as central components of AI-enabled transformation.

Fifth, the study extends research on strategic decision-making by conceptualizing AI as a co-constitutive actor in organizational cognition. AI systems increasingly participate in sensemaking and evaluation, shifting decision-making toward hybrid human–AI cognitive systems. This raises new theoretical questions regarding accountability, judgment, and control.

Together, these contributions are integrated into a unified framework of AI-enabled strategic alignment, linking capabilities, processes, and organizational context to explain how value is generated and sustained.

Table 3: Managerial Framework for Aligning AI with Business Strategy

Action Area	Key Managerial Steps
Strategic Alignment	Align AI initiatives with long-term organizational goals. - Continuously review and recalibrate AI investments. - Integrate AI strategy into overall business strategy.
Organizational Culture & Change Management	Foster innovation, adaptability, and digital readiness. - Communicate AI value clearly to reduce resistance. - Encourage cross-functional collaboration and experimentation.
Capability Development & Workforce Planning	Identify roles impacted by AI and plan reskilling/upskilling. - Enable collaboration between employees and AI tools. - Promote continuous learning ecosystems integrating human and AI capabilities.
Decision-Making & Governance	Use AI to enhance human judgment, not replace it. - Implement transparent, accountable, and ethical AI governance. - Monitor AI-driven systems for bias and unintended consequences.
Innovation & Value Creation	Leverage AI for operational efficiency, personalization, and market intelligence. - Explore AI-enabled product and service innovation. - Measure tangible and intangible value of AI initiatives.
Scenario Planning & Risk Management	Apply AI-driven simulations to anticipate disruptions. - Identify and mitigate ethical, social, and operational risks. - Develop strategies for AI-related strategic and operational risks.

Managerial Implications

The findings suggest that managerial approaches to AI must shift from implementation-focused logic to capability orchestration. AI adoption should not be treated as a deployment exercise, but as an ongoing process of aligning technology, decision systems, and organizational context.

AI-generated insights do not automatically translate into value; they require interpretive capacity, governance structures, and cultural readiness. This implies that investments in AI must be complemented by investments in organizational learning and decision integration.

Rather than attempting to eliminate tensions, managers should actively manage them – particularly those between automation and oversight, and between efficiency and strategic flexibility. Effective AI strategy therefore depends on balancing, rather than resolving, competing demands.

Table 3 summarizes these implications as a structured framework for aligning AI initiatives with business strategy.

CONCLUSION

This study shows that the strategic impact of AI depends less on technological sophistication than on the organizational capability to integrate, interpret, and align AI within dynamic socio-technical systems. By reconceptualizing AI as a capability-shaping mechanism, it advances a processual and theory-driven understanding of digital transformation.

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STRATEŠKO USKLAĐIVANJE SPOSOBNOSTI VEŠTAČKE INTELIGENCIJE SA POSLOVNOM STRATEGIJOM I STVARANJEM VREDNOSTI: SISTEMATSKI PREGLED LITERATURE IZ PERSPEKTIVE INFORMACIONIH SISTEMA

Veštačka inteligencija (AI) se sve više pozicionira kao strateški resurs, ali njen doprinos održivoj konkurentskoj prednosti i dalje ostaje neujednačen i teorijski fragmentiran. Ova studija se bavi tim jazom sprovođenjem sistematskog pregleda literature (SLR) koji obuhvata 79 radova na preseku veštačke inteligencije, informacionih sistema i poslovne strategije. Primenom konceptualno orijentisanog i teorijski usmerenog pristupa, pregled sintetiše postojeća istraživanja kako bi identifikovao ključne mehanizme, nedoslednosti i granične uslove koji oblikuju strateške ishode zasnovane na AI. Nalazi pokazuju da AI ne stvara vrednost kao samostalna tehnološka sposobnost, već kao deo šireg socio-tehničkog sistema koji zahteva usklađivanje između digitalnih sposobnosti, organizacionih procesa, upravljačkih struktura i kulture. Identifikovano je šest međusobno povezanih tematskih oblasti koje obuhvataju tehnološke osnove, stvaranje vrednosti, unapređenje zadataka, podršku odlučivanju, liderstvo i organizacionu integraciju. Analiza kroz studije ukazuje na trajne tenzije — kao što su automatizacija naspram ljudskog rasuđivanja i efikasnost naspram strateške fleksibilnosti — koje uslovljavaju realizaciju vrednosti zasnovane na AI. Na osnovu ovih uvida, studija razvija integrativni konceptualni model koji rekonceptualizuje strateško usklađivanje kao dinamičan proces zasnovan na sposobnostima i obeležen napetostima. Model pozicionira AI/IT sposobnosti kao mikrotemelje koji omogućavaju uočavanje, iskorišćavanje i rekonfiguraciju, uz naglašavanje posredničke uloge organizacione kulture i značaja strateške orkestracije. Studija doprinosi literaturi iz informacionih sistema i strateškog menadžmenta unapređujući konfiguracionu perspektivu stvaranja vrednosti zasnovane na AI, proširujući teoriju strateškog usklađivanja ka dinamičnom i paradoksno orijentisanom pogledu, i razrađujući mikrotemelje dinamičkih sposobnosti u kontekstu AI. Nalazi takođe pružaju primenljive smernice za organizacije koje nastoje da AI investicije pretvore u održivu stratešku vrednost.

Ključne reči: Veštačka inteligencija; Informacioni sistemi; Mašinsko učenje; Digitalna transformacija; Poslovna strategija; Inovacije