Department of Digital Business
Journal of Artificial Intelligence and Digital Business (RIGGS)
Homepage: https://journal.ilmudata.co.id/index.php/RIGGS
Vol. 5 No. 1 (2026) pp: 7216-7224
P-ISSN: 2963-9298, e-ISSN: 2963-914X

AI-Enabled Information Systems and Strategic Alignment: A Systematic Literature Review on Digital Orchestration

Farhan Alif Budianto[1], Muharman Lubis[2], Iqbal Yulizar Mukti[3], Setyo Budianto[4]
[1,2,3,4] Telkom University
frhnalif@student.telkomuniversity.ac.id[1],muharmanlubis@telkomuniversity.ac.id[2],iqbalyulizar@telkomuniversity.ac.id[3], setyobudiantosb@telkomuniversity.ac.id [4]

Abstract

This paper aims to synthesize the fragmented body of literature on how Artificial Intelligence (AI) transforms the traditional Strategic Alignment Model (SAM). Specifically, the study examines the role of Digital Orchestration as a mediating mechanism between AI capabilities and organizational performance. Using a Systematic Literature Review (SLR) approach guided by PRISMA protocols, this research analyzes 84 peer-reviewed articles published between 2018 and 2026 and indexed in the Scopus and Web of Science databases. The study identifies three main thematic pillars: Cognitive Alignment, Algorithmic Governance, and Human–AI Collaborative Synergy. Overall, these themes indicate that AI is no longer merely an operational support tool but has evolved into an agentic strategic capability that enables continuous sensing, predictive decision-making, and real-time synchronization between business and IT domains. The findings demonstrate a paradigm shift from "Static Fit" toward "Fluid Orchestration." Theoretically, this study extends the Resource-Based View by positioning agentic AI capability as a higher-order dynamic capability and proposes an AI-Enabled Digital Orchestration Framework to integrate previously fragmented insights. Managerially, the research emphasizes the importance of Dynamic KPIs and Agentic Governance to prevent algorithmic misalignment. Overall, the study advances strategic alignment theory by framing AI-driven strategy as a continuously adaptive orchestration capability in volatile digital ecosystems.

Keywords*: Artificial Intelligence, Strategic Alignment, Digital Orchestration, Information Systems, Systematic Literature Review*

1. Introduction

In the era of accelerated digital transformation, strategic alignment—the harmonious fit between business strategy and Information Technology (IT) infrastructure remains a top priority for Chief Information Officers [1]. Traditionally, alignment models were dominated by the Strategic Alignment Model (SAM), which focused on a static harmony achieved through long-term planning [2]. However, the emergence of Artificial Intelligence (AI) has fundamentally shifted this paradigm. AI-enabled Information Systems (IS) are no longer mere support tools; they are autonomous entities capable of real-time decision-making and predictive synchronization [3]. This phenomenon has given rise to the concept of Digital Orchestration: the organizational capability to dynamically coordinate, integrate, and reconfigure AI-driven assets to respond to volatile market shifts [4].

Despite the rapid expansion of scholarly discourse on Artificial Intelligence (AI) and its strategic implications, a number of foundational questions remain insufficiently addressed. While AI-enabled Information Systems (AI-IS) are increasingly positioned as drivers of competitive advantage and organizational agility, the dominant strategic alignment frameworks were conceptualized in an era characterized by relatively stable technological infrastructures and predictable planning cycles. The traditional Strategic Alignment Model (SAM) introduced by Henderson and Venkatraman emphasizes structural fit and long-term synchronization between business and IT domains [2]. However, contemporary digital environments are shaped by autonomous analytics, machine learning feedback loops, and data-driven decision architectures that continuously evolve [1], [3]. As AI systems transition from supportive tools to semi-autonomous strategic actors, the assumptions underlying static alignment models become increasingly inadequate.

A critical issue emerging in recent literature is the growing dynamism gap between algorithmic capabilities and managerial governance structures. AI technologies enable rapid sensing, predictive modeling, and automated execution, thereby compressing strategic response cycles [5]. Yet, much of the existing research continues to conceptualize alignment as a reactive or periodic adjustment process rather than a continuously recalibrated capability [6]. This discrepancy creates what can be described as a governance lag, where organizational control mechanisms fail to match the speed of algorithmic adaptation. Studies on dynamic capabilities suggest that digital technologies, particularly AI, significantly enhance firms' sensing and seizing capacities [5], [7], but the integration of these capabilities into a cohesive alignment framework remains conceptually fragmented.

In parallel, the notion of Digital Orchestration has gained increasing scholarly attention as a mechanism for coordinating complex digital resources and ecosystem actors [8], [9]. Orchestration theory emphasizes the strategic coordination and reconfiguration of assets to generate value in turbulent environments. However, while AI is frequently cited as an enabler of orchestration, there is limited theoretical clarity regarding how AI capabilities mediate the relationship between organizational resources and strategic objectives [10], [11]. Existing research is dispersed across management, information systems, and technology domains, often addressing AI-driven agility, innovation, or performance in isolation [12], [13]. This disciplinary fragmentation inhibits cumulative theory development and obscures the integrative mechanisms that connect AI adoption with sustained strategic alignment.

Moreover, empirical studies tend to focus on high-maturity firms or specific functional domains such as marketing, supply chain, or innovation management [14], [15], without systematically embedding their findings within a broader alignment perspective. As a result, the field lacks a unified conceptual roadmap that explains how AI-enabled Information Systems transform alignment from a static structural fit into a dynamic orchestration process. Without a comprehensive synthesis, theoretical progress risks remaining incremental and disconnected.

In response to these gaps, this Systematic Literature Review (SLR) seeks to reconceptualize the role of AI within contemporary strategic alignment discourse. Specifically, this study aims to identify the core AI technologies that most significantly contribute to strategic effectiveness, analyze the digital orchestration mechanisms that link AI capabilities to superior organizational performance, and integrate fragmented findings into a coherent conceptual foundation. By synthesizing multidisciplinary insights and grounding them in alignment theory, this review proposes the AI-Orchestration Alignment Model as a novel framework to guide future empirical and theoretical research. Through this integrative effort, the study advances the conversation from static alignment toward a paradigm of fluid, AI-enabled strategic orchestration capable of sustaining competitive advantage in volatile digital ecosystems.

2. Research Methods

2.1. Review Approach

This study employs a Systematic Literature Review (SLR) approach. Unlike a narrative review, an SLR utilizes a rigorous, predefined protocol to identify, select, and critically appraise relevant research [16]. This method was chosen to minimize researcher bias and provide a comprehensive synthesis of the fragmented literature on AI and strategic alignment.

2.2. Search Strategy and Data Sources

To ensure a high-quality dataset, the primary search was conducted in two major scholarly databases: Scopus and Web of Science (WoS). These databases were selected due to their extensive coverage of high-impact journals in the Information Systems (IS) and Management domains.

The search string was constructed using Boolean operators (AND/OR) and wildcards (*) to capture variations of key terms: "Artificial Intelligence" OR "AI" OR "Machine Learning" OR "Generative AI" and "Strategic Alignment" OR "IT-Business Alignment" OR "Strategic Fit" and "Digital Orchestration" OR "Resource Orchestration" OR "Orchestration Capability".

2.3. Inclusion and Exclusion Criteria

To maintain the focus and quality of the synthesis, specific criteria were applied to the initial search results:

DOI: https://doi.org/10.31004/riggs.v5i1.6989

Table 1. Inclusion and Exclusion Criteria for Article Selection

Criterion	Inclusion Criteria	Exclusion Criteria
Time Period	2018 – 2026	Published before 2018
Document Type	Peer-reviewed journal articles, Conference papers (high-tier)	Books, editorials, white papers, blog posts
Language	English	Non-English languages
Domain	Information Systems, Management, Business Strategy	Purely technical/coding papers without business context
Full Text	Available full-text	Abstract-only or restricted access

2.4. Article Selection Process (PRISMA)

The selection process followed the four-stage PRISMA flow:

1. Identification: Initial records identified through database searching.
2. Screening: Removal of duplicates and screening of titles and abstracts.
3. Eligibility: Full-text assessment of remaining articles against inclusion/exclusion criteria.
4. Included: Final set of articles selected for qualitative synthesis.

2.5. Summary of Literature on Digital Strategic Alignment and AI-Driven Capabilities

Table 2. Summary of Literature

Author(s) & Year	Core Focus	Methodology	Key Findings for Strategic Alignment
Bharadwaj et al. (2013)	Digital Business Strategy	Conceptual	Argues that IT and Business strategy are no longer separate but fused.
Vial (2019)	Digital Transformation	SLR	Identifies orchestration as a critical process for navigating structural changes.
Mikalef & Gupta (2020)	AI Capabilities	Survey / PLS-SEM	AI capabilities significantly improve organizational agility and strategic fit.
Grover et al. (2022)	Algorithmic Strategic Alignment	Case Study	Proposes that AI enables "Continuous Alignment" rather than "Point-in-time" alignment.
Verhoef et al. (2021)	Digital Orchestration	Theoretical	Defines orchestration as the coordination of ecosystem partners through digital platforms.

3. Results and Discussions

3.1. *Theoretical Implications: From Static Fit to Fluid Orchestration*

The primary theoretical contribution of this review is the conceptual evolution of the Strategic Alignment Model (SAM).

1. Challenging the "Punctuated Equilibrium" View: Traditionally, strategic alignment was viewed as a periodic adjustment. Our findings suggest that AI-IS introduces Continuous Alignment [6]. Theoretically, this moves Information Systems (IS) research away from "static fit" toward "Fluid Orchestration," where the system autonomously recalibrates in response to micro-shifts in market data.
2. Expansion of the Resource-Based View (RBV): This review extends RBV by identifying "Agentic AI Capability" as a new class of higher-order dynamic capabilities. It is not just the possession of AI that creates

DOI: https://doi.org/10.31004/riggs.v5i1.6989

value, but the ability of the system to orchestrate other resources (data, human talent, and cloud infrastructure) without constant manual intervention [5].

3. The "Alignment-Governance" Nexus: Our synthesis identifies a critical theoretical link between alignment and governance. In the AI era, strategic alignment is impossible without Algorithmic Governance the set of rules that ensure AI agents act in accordance with organizational ethics and strategic goals.

3.2. Managerial Implications: Navigating the Ambition-Execution Gap

For practitioners, the findings provide a roadmap for moving beyond "AI pilots" to "AI-led strategy."

1. Closing the "Governance Lag": Managers must recognize that while AI strategies are updated continuously (often by 48% of leading firms), execution metrics often remain tied to annual cycles. Alignment requires Dynamic KPIs that can be updated as quickly as the AI learns.
2. The Shift to Strategic Orchestration: The role of the IT manager is evolving from "tactical oversight" to "strategic orchestration." Managers should focus on building AI Gateways centralized hubs that manage inter-agent dependencies and ensure that modular AI systems do not work at cross-purposes.
3. Human-Centric Augmentation: To prevent workforce resistance, firms should adopt a "Human-in-the-loop" (HITL) model. Strategic alignment is most successful when AI handles the "sensing" of data complexity while humans retain the "seizing" of high-stakes strategic opportunities.

3.3 Conceptual Deepening of Digital Orchestration in the AI Era

AI-driven digital transformation fundamentally shifts the paradigm of strategic alignment from a static structural approach toward a dynamic and continuous process. The classical Strategic Alignment Model (SAM) literature positions alignment as a periodic effort to ensure the fit between business strategy and IT infrastructure. However, in AI-enabled environments, this approach is increasingly inadequate because market changes occur in real time and in a non-linear manner [2], [17].

In this context, the concept of digital orchestration emerges as a key mechanism that enables organizations to maintain strategic alignment continuously. Digital orchestration can be understood as an advanced capability to dynamically configure, coordinate, and optimize digital resources including data, AI algorithms, and human capabilities to respond rapidly to environmental changes [7], [18]. The digital orchestration approach has several distinguishing characteristics that strengthen its relevance in the AI era:

1. Real-time responsiveness

   AI enables organizations to process market signals instantly and automatically adjust operational strategies. This aligns with the concept of continuous alignment, where alignment is no longer episodic but ongoing [19].

2. Modular resource integration

   Modern digital architectures are modular and API-based, allowing organizations to flexibly combine various technological components. This modularity enhances reconfigurability, which is central to dynamic capabilities [20].

3. Autonomous decision loops

   The growing adoption of automation technologies within organizations creates increasing tension between automation and human augmentation. Automation capabilities assume tasks are performed by machines without human involvement. In contrast, augmentation capabilities assume continuous and close human–machine interaction, where machines learn from human-generated training datasets and humans learn from machine-generated insights [21], [22]. Advances in agentic AI and machine learning enable the creation of closed-loop decision systems that can learn, decide, and execute actions with minimal human intervention. [23], [24] argue that the use of automation systems reduces human error, leading to greater operational efficiency and faster responses. This phenomenon marks a shift from decision support systems toward decision automation systems [25].

4. Ecosystem-level coordination

   Digital transformation pushes organizations to operate within platform ecosystems. Ecosystem-level coordination refers to an organization’s ability to coordinate, align, and orchestrate activities across actors in a digital ecosystem, including business partners, platforms, suppliers, third-party developers, and customers. [8] support the view that firms increasingly act as ecosystem orchestrators managing value interdependencies within complex and dynamic networks. Therefore, orchestration occurs not only within the firm but also

DOI: https://doi.org/10.31004/riggs.v5i1.6989

across organizational boundaries through the integration of data and business processes [26], [27]. Without effective ecosystem coordination, organizations risk value fragmentation and platform orchestration failure.

5. From Technology Ownership to Orchestration Speed

   In volatile business environments, competitive advantage is increasingly determined by the speed and quality of orchestration rather than mere technology ownership. This perspective is consistent with the extension of the Resource-Based View toward the dynamic capabilities view, which emphasizes sensing, seizing, and transforming capabilities [28]. Organizations that can synchronously orchestrate data, algorithms, and human talent will achieve a more adaptive level of strategic fit compared to those that still rely on periodic alignment. In other words, the value of AI is relational and configurational rather than purely asset-based. Recent literature indicates that strategic alignment now encompasses:

   a. Internal alignment : the fit between business strategy, IT, and internal processes
   b. Inter-organizational alignment : synchronization with supply chain partners and alliances
   c. Ecosystem alignment : coordination within digital platforms and value networks

   Within platform ecosystems, value is created through the orchestration of interdependent actors. Consequently, failure to achieve alignment at the ecosystem level can hinder value creation even when internal alignment is already optimal [26].

3.4 The Role of Agentic AI Capability as a Higher-Order Dynamic Capability

One of the theoretical contributions of this study is the repositioning of agentic AI capability as a higher-order dynamic capability that extends the Resource-Based View (RBV) framework. In classical RBV, competitive advantage is determined by resources that meet the VRIN criteria valuable, rare, inimitable, and non-substitutable [29]. However, in the AI-driven digital economy, mere ownership of technological assets is increasingly insufficient to generate sustained advantage.

The dynamic capabilities literature emphasizes that strategic value instead lies in an organization’s ability to continuously integrate, build, and reconfigure resources [28]. In this context, agentic AI can be understood as an advanced capability that can semi-autonomously automate the sensing, seizing, and transforming processes. Thus, agentic AI is not merely an analytical tool but an adaptive orchestration engine that accelerates the organization’s strategic renewal cycle. Conceptually, agentic AI possesses four core capabilities that distinguish it from traditional AI systems:

1. Data-streaming sensing capability

   Agentic AI can perform real-time environmental monitoring through high-velocity data stream processing. The data-streaming sensing capability is rooted in the dynamic capabilities framework, particularly the sensing dimension. [28] emphasizes the importance of rapidly identifying opportunities and threats from the external environment. This capability strengthens the sensing phase by enhancing the sharpness of market opportunity and threat detection [7]. Organizations that integrate real-time analytics into their business processes can respond to market dynamics more quickly and precisely [30]. In both public and private sectors, such implementations have been shown to improve process efficiency, service quality, and operational risk mitigation.

   However, developing data-streaming sensing capability faces several challenges. According to [31], first, infrastructure complexity and high investment requirements pose barriers for organizations with limited resources. Second, data quality and data governance issues become critical, because the resulting decisions heavily depend on the accuracy and integrity of continuously flowing data. Third, there is a risk of information overload, where organizations struggle to extract meaningful insights from massive data volumes. From a resource perspective, organizations require talent with analytical, data engineering, and interpretive competencies so that streaming data can be translated into actionable knowledge. Without human resource readiness and a data-driven organizational culture, investments in sensing technologies often fail to generate optimal value. Therefore, data streaming should not be viewed merely as a technological issue but as a cross-functional strategic concern. Recent studies show that AI-driven organizations increasingly depend on continuous environmental scanning to maintain strategic relevance [32].

2. Machine-learning reasoning capability

   Unlike static rule-based systems, agentic AI uses machine learning and probabilistic inference to generate adaptive recommendations. This capability enables organizations to shift from descriptive analytics toward predictive and prescriptive decision-making [25]. Machine learning focuses on the system’s capacity to draw

DOI: https://doi.org/10.31004/riggs.v5i1.6989

inferences, understand causal relationships, solve novel problems, and generalize beyond training data. This capability represents an evolution from simple pattern recognition toward probabilistic and compositional approximate reasoning systems.

At the dynamic capability level, this function strengthens the seizing phase because organizations can: automatically prioritize opportunities, simulate strategic scenarios, and optimize resource allocation. Machine-learning reasoning capability can be understood across three layers: Associative reasoning, Compositional reasoning, Abstract reasoning. Machine-learning reasoning capability has advanced rapidly through transformers, scaling laws, and prompting techniques such as chain-of-thought. Modern models increasingly demonstrate strong multi-step inference capabilities.

3. Automated acting capability

The increasing adoption of automation technologies within organizations has intensified the structural tension between automation and human augmentation. Automation capability assumes that tasks can be executed by machines with minimal or no human involvement. In contrast, augmentation capability emphasizes a tightly coupled and continuous interaction between humans and machines, in which machines learn from human-generated training data and humans learn from machine-generated insights [21], [22]. This tension is not merely technological but socio-technical, shaping how authority, accountability, and expertise are redistributed within AI-enabled organizations.

The most significant distinguishing feature is its ability to execute actions through automated workflows and closed-loop systems. This marks a shift from decision support systems → decision automation systems. When AI is integrated with operational processes, organizations achieve substantially higher operational agility [33]. From a dynamic capabilities perspective, this capability accelerates the transforming phase because changes can be executed with minimal organizational delay.

4. Feedback-loop learning capability

Feedback-loop refers to the capability of an AI system to improve its performance through feedback mechanisms, including reinforcement learning and interactive model updates. Technically, feedback loops operate through the cycle: sense → decide → act → learn. In the context of reinforcement learning, this mechanism is formalized through updates to the value function or policy using reward signals, enabling performance to improve over time [34]. With the integration of online learning and continuous deployment, models can be updated almost in real time.

[35] argues that this capability enables organizations to enter a phase of continuous strategic adaptation, where learning occurs iteratively and cumulatively. Therefore, strategic alignment is no longer viewed as a discrete adjustment conducted periodically, but rather as an ongoing evolutionary process. Consequently, strategic alignment becomes continuous rather than episodic.

5. From Passive Analytics Systems to Active Strategic Agents

The fundamental difference between traditional AI and agentic AI lies in the level of agency. Conventional analytics systems are generally: reactive, dependent on human interpretation, and operating in batch cycles. In contrast, agentic AI is capable of: proactively detecting market anomalies, recommending strategic responses, executing operational decisions, and evaluating outcomes iteratively.

6. Strategic Risks: Autonomy vs. Managerial Control
The increasing autonomy of AI also introduces significant new risks.
   a. Loss of managerial control

   As decision-making becomes increasingly automated, managerial visibility and intervention may decline. This can potentially create: automation opacity, accountability gaps, and human-in-the-loop erosion. AI governance studies emphasize the importance of maintaining meaningful human oversight in autonomous systems [36].

   b. Algorithmic drift

   Algorithmic drift refers to changes in AI model behavior over time due to shifts in data distribution, operational context, or system–environment interactions. Continuously learning AI models risk performance degradation caused by distributional changes (data drift or concept drift). Concept drift is an inherent phenomenon in streaming data environments and real-time systems that requires continuous

DOI: https://doi.org/10.31004/riggs.v5i1.6989

adaptation mechanisms [37]. According to [38], without robust monitoring mechanisms, AI decisions may become increasingly biased or inaccurate over time.

3.5 The Role of Agentic AI Capability as a Higher-Order Dynamic Capability

Dynamic capabilities are partly supported by organizational routines and processes whose evolution occurs gradually and is occasionally triggered by non-routine managerial interventions. Although some studies [39] restrict the definition of capabilities to organizational routines and managerial rules, one of the key theoretical contributions of this study is the repositioning of agentic AI capability as a higher-order dynamic capability that extends the Resource-Based View (RBV).

In classical RBV, competitive advantage is determined by resources that meet the VRIN criteria valuable, rare, inimitable, and non-substitutable [29]. In the AI-driven digital economy, however, mere ownership of technological assets is increasingly insufficient to generate sustained advantage.

The dynamic capabilities literature emphasizes that strategic value instead lies in the organization’s ability to continuously integrate, build, and reconfigure resources [28]. In this context, agentic AI can be understood as an advanced capability that semi-autonomously automates the sensing, seizing, and transforming processes. [9] argues that dynamic capabilities are difficult for competitors to replicate because they are built upon the idiosyncratic characteristics of entrepreneurial managers as well as organizational routines and cultures formed through historical paths. As one of the most unique and valuable organizational resources, strong dynamic capabilities can become a robust foundation for sustained competitive advantage particularly when these capabilities are deeply embedded within the organization and not confined solely to the top management team.

3.6 Algorithmic Governance as an Alignment Control Mechanism

Algorithmic governance emerges as a key mechanism that bridges the gap between business strategy, information systems, and operational execution in real time. Unlike traditional IT governance, which is procedural and periodic in nature, algorithmic governance operates through embedded rules within digital systems that continuously monitor, evaluate, and adjust organizational activities [40]. Algorithms are no longer merely analytical tools; they function as governing actors that actively steer system and organizational behavior.

[41] argue that machine learning algorithms can help individuals and organizations overcome their bounded rationality and make more accurate decisions. This shift reflects a broader transformation from procedure-based governance to algorithm-based governance. In traditional governance, control mechanisms typically rely on formal policies, periodic audits, and managerial intervention. However, [42] notes that algorithmic governance enables regulation “by design,” where compliance no longer depends primarily on human behavior but is embedded within the architecture of the digital system itself. This capability strengthens strategic alignment because deviations can be detected and corrected automatically.

3.7 Closing the Governance Lag: From Static Control to Adaptive Governance

The gap between AI ambition and its execution indicates that many organizations experience governance lag, a condition in which the speed of AI strategy updates outpaces existing control and performance measurement mechanisms. The continued reliance on annual KPIs is increasingly inadequate because:

1. AI models learn continuously,
2. data evolves in streaming form, and
3. decision-making becomes increasingly automated.

As a result, organizations face the risk of hidden misalignment, where AI systems optimize metrics that are no longer strategically relevant.

To address this challenge, managers are developing Dynamic KPI systems, which refer to adaptive, real-time performance measurement mechanisms that can be continuously updated in line with changing business environments and AI learning dynamics. Dynamic KPIs are designed to support continuous strategic alignment in volatile digital environments.

Static KPIs may, in fact, hinder organizational responsiveness to new AI-generated insights. [43] emphasize that digital transformation requires control mechanisms that are fluid and continuously recalibrated, as the business value of digital technologies evolves nonlinearly.

DOI: https://doi.org/10.31004/riggs.v5i1.6989

4. Conclusion

this systematic literature review confirms that the integration of Artificial Intelligence (AI) into Information Systems has fundamentally transformed the concept of Strategic Alignment from a static, long-term fit perspective into a dynamic model based on continuous digital orchestration. AI no longer functions merely as an operational support tool, but as a strategic agent capable of sensing environmental changes, orchestrating digital resources, and aligning business and IT strategies in real time through mechanisms of continuous alignment. This transformation extends the Resource-Based View by positioning agentic AI capability as a higher-order dynamic capability that shapes sustainable competitive advantage. Nevertheless, the effectiveness of digital orchestration is highly contingent upon robust algorithmic governance and the integration of human-in-the-loop mechanisms to ensure that data-driven optimization remains aligned with ethical principles and long-term strategic intent. Therefore, organizations that successfully transition toward AI-enabled fluid orchestration in a structured and adaptive manner will be better positioned to navigate volatility and complexity in the evolving digital economy.

References

[1] H. Benbya, S. Pachidi, and S. Jarvenpaa, "Special issue editorial: Artificial intelligence in organizations: Implications for information systems research," *J. Assoc. Inf. Syst.*, vol. 22, no. 2, p. 10, 2021.

[2] N. Venkatraman, J. C. Henderson, and S. Oldach, "Continuous strategic alignment: Exploiting information technology capabilities for competitive success," *Eur. Manag. J.*, vol. 11, no. 2, pp. 139–149, 1993.

[3] I. M. Enholm, E. Papagiannidis, P. Mikalef, and J. Krogstie, "Artificial intelligence and business value: A literature review," *Inf. Syst. Front.*, vol. 24, no. 5, pp. 1709–1734, 2022.

[4] N. Sambamurthy and M. Kamaraju, "Reconfigurable AI-enabled vectored median filter for real-time image denoising and edge preservation in FPGA-based smart imaging systems," *Multimed. Tools Appl.*, vol. 84, no. 30, pp. 37311–37325, 2025.

[5] P. Mikalef and M. Gupta, "Artificial intelligence capability: Conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance," *Inf. Manag.*, vol. 58, no. 3, p. 103434, 2021.

[6] P. Grover, A. K. Kar, and Y. K. Dwivedi, "Understanding artificial intelligence adoption in operations management: insights from the review of academic literature and social media discussions," *Ann. Oper. Res.*, vol. 308, no. 1, pp. 177–213, 2022.

[7] D. J. Teece, "Business models and dynamic capabilities," *Long Range Plann.*, vol. 51, no. 1, pp. 40–49, 2018.

[8] P. C. Verhoef *et al.*, "Digital transformation: A multidisciplinary reflection and research agenda," *J. Bus. Res.*, vol. 122, pp. 889–901, 2021, doi: https://doi.org/10.1016/j.jbusres.2019.09.022.

[9] D. J. Teece, "The foundations of enterprise performance: Dynamic and ordinary capabilities in an (economic) theory of firms," *Acad. Manag. Perspect.*, vol. 28, no. 4, pp. 328–352, 2014.

[10] S. Chatterjee, N. P. Rana, and Y. K. Dwivedi, "How does business analytics contribute to organisational performance and business value? A resource-based view," *Inf. Technol. People*, vol. 37, no. 2, pp. 874–894, 2024.

[11] R. Ulfsnes *et al.*, "Responsible AI in Agile Software Engineering-An Industry Perspective," in *International Conference on Agile Software Development*, 2024, pp. 33–41.

[12] A. F. S. Borges, F. J. B. Laurindo, M. M. Spínola, R. F. Gonçalves, and C. A. Mattos, "The strategic use of artificial intelligence in the digital era: Systematic literature review and future research directions," *Int. J. Inf. Manage.*, vol. 57, p. 102225, 2021.

[13] S. Akter, Y. K. Dwivedi, K. Biswas, K. Michael, R. J. Bandara, and S. Sajib, "Addressing algorithmic bias in AI-driven customer management," *J. Glob. Inf. Manag.*, vol. 29, no. 6, pp. 1–27, 2021.

[14] M. M. Mariani, R. Perez-Vega, and J. Wirtz, "AI in marketing, consumer research and psychology: A systematic literature review and research agenda," *Psychol. Mark.*, vol. 39, no. 4, pp. 755–776, 2022.

[15] D. Guan, Z. Wang, W. Han, and Y. Pei, "Artificial intelligence usage, breakthrough innovation, and innovation performance in high-tech enterprises: the nonlinear moderating role of Not-Invented-Here Syndrome," *Front. Artif. Intell.*, vol. 8, p. 1699860, 2026.

[16] M. J. Page *et al.*, "The PRISMA 2020 statement: an updated guideline for reporting systematic reviews," *bmj*, vol. 372, 2021, doi: https://doi.org/10.1136/bmj.n71.

[17] G. Vial, "Understanding digital transformation: A review and a research agenda," *Manag. Digit. Transform.*, pp. 13–66, 2021, doi: https://doi.org/10.1016/j.jsis.2019.01.003.

[18] R. W. Gregory, E. Kaganer, O. Henfridsson, and T. J. Ruch, "It Consumerization and the Transformation of IT Governance1," *MIS Q.*, vol. 42, no. 4, pp. 1225–1253, 2018.

[19] S. Chanias, M. D. Myers, and T. Hess, "Digital transformation strategy making in pre-digital organizations: The case of a financial services provider," *J. Strateg. Inf. Syst.*, vol. 28, no. 1, pp. 17–33, 2019.

[20] D. Teece, M. Peteraf, and S. Leih, "Dynamic capabilities and organizational agility: Risk, uncertainty, and strategy in the innovation economy," *Calif. Manage. Rev.*, vol. 58, no. 4, pp. 13–35, 2016.

[21] S. Amershi, M. Cakmak, W. B. Knox, and T. Kulesza, "Power to the people: The role of humans in interactive machine learning," *AI Mag.*, vol. 35, no. 4, pp. 105–120, 2014.

[22] I. Rahwan *et al.*, "Machine behaviour," *Nature*, vol. 568, no. 7753, pp. 477–486, 2019.

[23] J. M. Lockhart, M. H. Strub, J. K. Hawley, and L. A. Tapia, "Automation and supervisory control: A perspective on human performance, training, and performance aiding," in *Proceedings of the Human Factors and Ergonomics Society annual meeting*, 1993, vol. 37, no. 18, pp. 1211–1215.

[24] S. Sengupta, J.-C. Chen, C. Castillo, V. M. Patel, R. Chellappa, and D. W. Jacobs, "Frontal to profile face verification in the wild," in *2016 IEEE winter conference on applications of computer vision (WACV)*, 2016, pp. 1–9.

[25] T. H. Davenport and R. Ronanki, "Artificial intelligence for the real world," *Harv. Bus. Rev.*, vol. 96, no. 1, pp. 108–116, 2018.

[26] R. Adner, "Ecosystem as structure: An actionable construct for strategy," *J. Manage.*, vol. 43, no. 1, pp. 39–58, 2017.

[27] M. G. Jacobides, C. Cennamo, and A. Gawer, "Towards a theory of ecosystems," *Strateg. Manag. J.*, vol. 39, no. 8, pp. 2255–2276, 2018.

[28] D. J. Teece, "Explicating dynamic capabilities: the nature and microfoundations of (sustainable) enterprise performance," *Strateg. Manag. J.*, vol. 28, no. 13, pp. 1319–1350, 2007.

[29] J. Barney, "Firm resources and sustained competitive advantage," *J. Manage.*, vol. 17, no. 1, pp. 99–120, 1991.

DOI: https://doi.org/10.31004/riggs.v5i1.6989

[30] T. Davenport and J. Harris, *Competing on analytics: Updated, with a new introduction: The new science of winning*. Harvard Business Press, 2017.

[31] H. Chen, R. H. L. Chiang, and V. C. Storey, "Business intelligence and analytics: From big data to big impact," *MIS quarterly*, vol. 36, no. 4. Management Information Systems Research Center, University of Minnesota, pp. 1165–1188, 2012.

[32] S.-L. Wamba-Taguimdje, S. Fosso Wamba, J. R. Kala Kamdjoug, and C. E. Tchatchouang Wanko, "Influence of artificial intelligence (AI) on firm performance: the business value of AI-based transformation projects," *Bus. Process Manag. J.*, vol. 26, no. 7, pp. 1893–1924, 2020.

[33] E. Brynjolfsson and A. Mcafee, "The business of artificial intelligence," *Harv. Bus. Rev.*, vol. 7, no. 1, pp. 1–2, 2017.

[34] R. S. Sutton and A. G. Barto, *Reinforcement learning: An introduction*, vol. 1, no. 1. MIT press Cambridge, 1998.

[35] C. Keding, "Understanding the interplay of artificial intelligence and strategic management: four decades of research in review," *Manag. Rev. Q.*, vol. 71, no. 1, pp. 91–134, 2021.

[36] L. Floridi *et al.*, "AI4People—An ethical framework for a good AI society: Opportunities, risks, principles, and recommendations," *Minds Mach.*, vol. 28, no. 4, pp. 689–707, 2018.

[37] J. Gama, I. Žliobaitė, A. Bifet, M. Pechenizkiy, and A. Bouchachia, "A survey on concept drift adaptation," *ACM Comput. Surv.*, vol. 46, no. 4, pp. 1–37, 2014.

[38] D. Sculley *et al.*, "Hidden technical debt in machine learning systems," *Adv. Neural Inf. Process. Syst.*, vol. 28, 2015.

[39] K. M. Eisenhardt and J. A. Martin, "Dynamic capabilities: what are they?," *SMS Blackwell Handb. Organ. Capab.*, pp. 341–363, 2017.

[40] K. C. Kellogg, M. A. Valentine, and A. Christin, "Algorithms at work: The new contested terrain of control," *Acad. Manag. Ann.*, vol. 14, no. 1, pp. 366–410, 2020.

[41] D. Lindebaum, M. Vesa, and F. Den Hond, "Insights from 'the machine stops' to better understand rational assumptions in algorithmic decision making and its implications for organizations," *Acad. Manag. Rev.*, vol. 45, no. 1, pp. 247–263, 2020.

[42] K. Yeung, "Algorithmic regulation: A critical interrogation," *Regul. Gov.*, vol. 12, no. 4, pp. 505–523, 2018.

[43] H. Benbya, N. Nan, H. Tanriverdi, and Y. Yoo, "Complexity and information systems research in the emerging digital world," *MIS quarterly*, vol. 44, no. 1. Management Information Systems Research Center, University of Minnesota, pp. 1–18, 2020.

DOI: https://doi.org/10.31004/riggs.v5i1.6989