Vol. 7, No. 1, 2026, pp. 379-391
DOI: https://doi.org/10.29210/991810

Contents lists available at Elora Center

Lentera Negeri

Journal homepage: https://lentera.eloracenter.org/lentera

Microfoundations of dynamic capabilities in artificial intelligence adoption for competitive advantage

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Article Info

Article history:
Received May 4th, 2026
Revised Jun 11th, 2026
Accepted Jun 17th, 2026

Keywords:
Dynamic capabilities
Artificial intelligence
Microfoundations
Competitive advantage
Strategic management

ABSTRACT

This study explored the role of dynamic capabilities in enhancing corporate competitive advantage through the integration of artificial intelligence and managerial microfoundations. The research addressed the growing need for organizations to adapt to rapid technological changes and increasingly complex competitive environments. Using a qualitative literature review design, this study systematically analyzed 42 peer-reviewed sources retrieved from Scopus, Web of Science, ScienceDirect, SpringerLink, and Google Scholar. Sources were selected based on their relevance to dynamic capabilities, AI adoption, and microfoundational perspectives in strategic management. Data were analyzed using qualitative content analysis and thematic analysis. The findings revealed that the reviewed literature consistently indicates that dynamic capabilities, operationalized through sensing, seizing, and reconfiguring processes, are enhanced by the integration of AI technologies. However, the results also showed that the effectiveness of these capabilities depended heavily on managerial cognition, skills, and decision-making capacity. The study revealed that AI functioned not as a standalone driver of competitive advantage, but as an embedded component within organizational capabilities that required human interpretation and strategic alignment. Furthermore, variations in organizational outcomes highlighted the importance of micro-level factors in determining the success of technology adoption. The study concluded that the interplay between technological capabilities and human agency was essential for achieving sustainable competitive advantage. These findings contributed to a more comprehensive understanding of strategic management in the digital era and provided insights for both academic development and managerial practice.

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Introduction

In the contemporary business environment characterized by rapid technological disruption and increasing global competition, organizations are compelled to continuously adapt their internal capabilities to sustain competitive advantage. The emergence of artificial intelligence (AI) as a transformative technological force has fundamentally reshaped how firms create, manage, and leverage strategic resources. AI adoption enables organizations to process vast amounts of data, enhance decision-making accuracy, and automate complex processes, thereby redefining traditional competitive dynamics (Brynjolfsson & Mcafee, 2017). Furthermore, digital technologies increasingly reshape innovation processes and organizational structures, requiring firms to continuously develop new capabilities to exploit emerging technological opportunities and sustain competitive advantage (Nambisan et al., 2017). Recent studies further suggest that AI has become a central component of broader digital transformation initiatives, enabling organizations to redesign business processes, enhance customer value creation, and improve organizational adaptability in dynamic environments (Verhoef et al., 2021; Vial, 2021). Within this context, the concept of dynamic capabilities has gained renewed attention as a critical theoretical lens to understand how firms integrate, build, and reconfigure internal and external competencies in response to changing environments (Bleady et al., 2018; Konlechner et al., 2018). However, while dynamic capabilities provide a macro-level explanation, there remains a need to explore the underlying individual-level mechanisms that drive these capabilities, particularly in the era of AI.

Dynamic capabilities theory emphasizes three core processes—sensing, seizing, and reconfiguring—that enable firms to respond effectively to environmental changes (Matysiak et al., 2018). Prior studies have extensively examined the relationship between dynamic capabilities and firm performance, demonstrating that firms with strong dynamic capabilities tend to achieve superior competitive advantage (Eisenhardt & Martin, 2000; Ferreira et al., 2021). Furthermore, recent research has begun to integrate digital transformation and AI into this framework, suggesting that technological capabilities can enhance the effectiveness of dynamic capabilities (Warner & Wäger, 2019). Despite these advancements, much of the existing literature remains focused on organizational-level constructs, often overlooking the micro-level foundations that underpin the development and deployment of dynamic capabilities.

The concept of microfoundations has emerged as a promising approach to address this limitation by examining the individual actions, interactions, and decision-making processes that shape organizational capabilities (Foss, 2016; Mohamed & Karoui Zouaoui, 2026). Microfoundational perspectives argue that organizational capabilities ultimately originate from the knowledge, cognition, and actions of individual actors whose decisions collectively shape firm-level outcomes. Managerial cognitive capabilities influence how decision makers perceive environmental changes, interpret strategic opportunities, and mobilize organizational resources to support capability development (Helfat & Peteraf, 2015). In the context of AI adoption, managerial decision-making becomes even more critical due to the complexity, uncertainty, and ethical considerations associated with AI technologies (Raisch & Krakowski, 2021). However, empirical research integrating microfoundations, dynamic capabilities, and AI adoption remains limited, particularly in emerging markets where organizational structures and technological readiness differ significantly from developed economies.

This gap in the literature presents a significant research opportunity. While recent studies acknowledge that AI capability can enhance organizational performance and dynamic capabilities (Brynjolfsson et al., 2021), findings remain inconclusive regarding the mechanisms through which AI-generated insights are translated into strategic actions. Recent research suggests that AI may simultaneously strengthen organizational sensing and decision-making capabilities while creating risks associated with algorithmic rigidity, reduced managerial discretion, and path dependency in strategic adaptation (Raisch & Krakowski, 2021). These contradictory findings indicate that macro-level dynamic capabilities theory alone may not sufficiently explain how organizations transform AI investments into sustainable competitive advantage. Consequently, a deeper examination of micro-level mechanisms is required, particularly managerial cognition, which shapes how AI-driven information is interpreted, evaluated, and incorporated into organizational decision-making processes.

This fragmented perspective limits our understanding of how firms can effectively leverage AI to develop dynamic capabilities and achieve sustainable competitive advantage. Therefore, this study addresses this critical gap by proposing an integrative framework that positions managerial cognition as a mediating variable linking AI capability to dynamic capabilities and ultimately to competitive advantage.

The novelty of this research lies in its microfoundational perspective, which shifts the analytical focus from organizational-level outcomes toward the cognitive mechanisms underlying strategic decision-making. Prior studies have predominantly examined the direct relationship between AI capability, dynamic capabilities, and competitive advantage, assuming that technological resources automatically generate superior organizational outcomes. However, such approaches provide limited explanation regarding how managers interpret AI-generated insights and transform them into strategic actions. This study proposes managerial cognition as a mediating mechanism linking AI capability and dynamic capabilities, thereby explaining the cognitive processes through which technological resources contribute to sensing, seizing, and reconfiguring activities. By doing so, this study extends the dynamic capabilities framework beyond resource-level explanations and highlights the role of human agency in AI-enabled strategic transformation.

Conceptual Framework and Hypothesis Development

Based on the identified research gaps and theoretical foundations, this study proposes an integrative conceptual framework that explains how artificial intelligence (AI) capability contributes to competitive advantage through dynamic capabilities, with managerial cognition acting as a key mediating mechanism. This framework extends the dynamic capabilities perspective by incorporating a microfoundational lens, emphasizing the role of managerial cognitive processes in translating technological potential into strategic outcomes.

AI capability is conceptualized as a firm's ability to acquire, deploy, integrate, and leverage artificial intelligence technologies, data resources, analytical infrastructures, and organizational expertise to support prediction, learning, decision-making, and strategic adaptation. This capability encompasses multiple dimensions, including data management capability, analytical capability, technological infrastructure, algorithmic deployment capability, and human expertise required to interpret AI-generated outputs. Consequently, the effectiveness of AI capability depends not only on technological sophistication but also on the organization's ability to combine AI resources with managerial knowledge and strategic objectives. Recent empirical studies demonstrate that AI capability extends beyond technological infrastructure and includes the organizational ability to integrate analytical resources, managerial expertise, and collaborative networks to support strategic decision-making and organizational performance (Dubey et al., 2021; Mikalef & Gupta, 2021).

Furthermore, dynamic capabilities are widely recognized as a key driver of competitive advantage, as they enable firms to adapt to environmental changes, innovate, and reconfigure resources efficiently. At the same time, managerial cognition is also expected to directly influence competitive advantage, reflecting the importance of human agency in strategic decision-making. The proposed relationships among variables are illustrated in Figure 1.

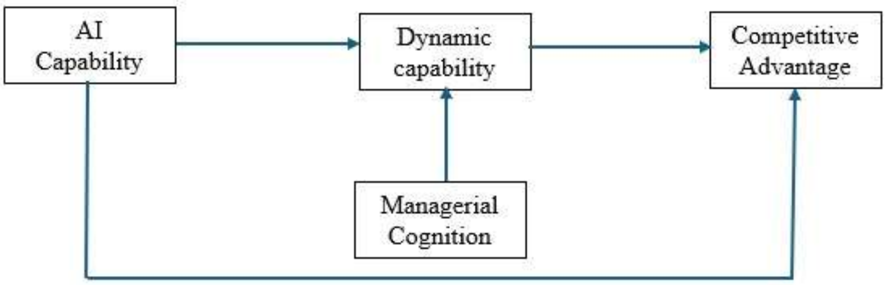

Figure 1 <Proposed Conceptual Framework with the Mediating Role of Managerial Cognition>

As illustrated in Figure 1, this study proposes that AI capability influences dynamic capabilities both directly and indirectly through managerial cognition. Managerial cognition serves as a mediating mechanism that enables managers to interpret AI-driven insights and translate them into strategic actions within sensing, seizing, and reconfiguring processes. Furthermore, dynamic capabilities are expected to enhance competitive advantage, while managerial cognition also contributes directly to competitive outcomes. This framework highlights that the transformation of technological capability into competitive advantage is fundamentally dependent on human cognitive processes.

Based on the proposed conceptual framework, this study formulates several hypotheses to explain the relationships among artificial intelligence capability, managerial cognition, dynamic capabilities, and competitive advantage: (1) H_1: Artificial intelligence capability has a positive effect on dynamic capabilities; (2) H_2: Dynamic capabilities have a positive effect on competitive advantage; (3) H_3: Artificial intelligence capability has a positive effect on managerial cognition; (4) H_4: Managerial cognition has a positive effect on dynamic capabilities; (5) H_5: Managerial cognition has a positive effect on competitive advantage; (6) H_6: Managerial cognition mediates the relationship between artificial intelligence capability and dynamic capabilities.

The objective of this study is to synthesize and critically analyze existing literature on the relationships among AI capability, managerial cognition, dynamic capabilities, and competitive advantage. Specifically, this study aims to compare existing theoretical perspectives, identify recurring empirical patterns, and develop an integrative conceptual framework explaining how managerial cognition mediates the relationship between AI capability and dynamic capabilities. The unit of analysis adopted in this review encompasses both organizational-level capabilities and managerial-level cognitive processes, allowing a multi-level understanding of AI-enabled competitive advantage.

The urgency of this research is further amplified by the increasing reliance on AI across industries and the growing complexity of competitive environments. Organizations that fail to effectively integrate AI into their strategic processes risk losing their competitive edge. At the same time, the successful adoption of AI requires not only technological investment but also the development of managerial capabilities that can interpret data-driven insights and translate them into strategic actions (Mikalef et al., 2020). Therefore, understanding the microfoundations of dynamic capabilities in AI adoption is essential for both academic advancement and practical application.

Building on this context, this study aims to investigate how microfoundations influence the development of dynamic capabilities in the process of AI adoption and how these capabilities contribute to corporate competitive advantage. Specifically, the research seeks to answer the following critical question: how do managerial-level processes shape the effectiveness of dynamic capabilities in leveraging AI for competitive advantage? By addressing this question, the study contributes to bridging the gap between macro-level strategic management theories and micro-level organizational behavior perspectives.

The novelty of this research lies in its integrative approach, combining three important but often separately studied domains: dynamic capabilities, artificial intelligence adoption, and microfoundations. Unlike previous studies that focus primarily on organizational-level analysis, this research emphasizes the role of individual actors, particularly managers, in shaping strategic outcomes. Furthermore, the study extends the dynamic capabilities framework by incorporating AI as a central component, thereby providing a more contemporary and relevant understanding of competitive advantage in the digital era.

The expected contributions of this study are both theoretical and practical. Theoretically, it advances the dynamic capabilities literature by incorporating microfoundational perspectives and digital technologies, offering a more holistic framework for understanding competitive advantage. Practically, the findings can provide valuable insights for managers and policymakers on how to develop and leverage AI-driven capabilities effectively. Additionally, this research may serve as a foundation for future studies exploring the intersection of technology, strategy, and organizational behavior.

In conclusion, this study addresses a critical gap in the literature by examining the microfoundations of dynamic capabilities in AI adoption and their impact on corporate competitive advantage. By moving from a general understanding of dynamic capabilities to a more nuanced analysis of individual-level processes, this research offers a deeper and more comprehensive perspective on how firms can navigate the complexities of the digital age. Furthermore, it opens new avenues for future research, particularly in exploring the interplay between human and technological capabilities in shaping organizational success.

Method

This study employs a qualitative research approach using a literature study design to explore the microfoundations of dynamic capabilities in artificial intelligence (AI) adoption and their role in enhancing corporate competitive advantage. A qualitative literature study is considered appropriate because the objective of this research is to synthesize, interpret, and critically analyze existing theoretical and empirical findings rather than to generate primary data. This approach allows for a comprehensive understanding of the relationships among dynamic capabilities, AI adoption, and managerial microfoundations by integrating insights from prior studies (Snyder, 2019).

The population of this study consists of scholarly works related to dynamic capabilities, artificial intelligence, and microfoundations in strategic management. The sampling technique used is purposive sampling, where only highly relevant, peer-reviewed journal articles, books, and reputable academic reports published primarily within the last 10–15 years are selected. Inclusion criteria include studies that directly address dynamic capabilities theory, AI adoption or digital transformation, managerial cognition, and microfoundational perspectives. Studies were included if they provided either theoretical explanations or empirical evidence concerning the relationships among AI capability, dynamic capabilities, managerial cognition, and competitive advantage. Exclusion criteria included non-peer-reviewed publications, conference abstracts, duplicate records, studies lacking methodological transparency, and publications not directly related to the research objectives.

The data sources in this study are secondary data derived from academic databases such as Scopus, Web of Science, ScienceDirect, SpringerLink, and Google Scholar. These sources were selected due to their credibility and broad coverage of high-quality scholarly publications. Key search keywords included "dynamic capabilities," "artificial intelligence," "AI capability," "microfoundations," "managerial cognition," "competitive advantage," and "digital transformation." Boolean operators (AND, OR, NOT) were used to refine search results and improve relevance.

The literature selection process followed a systematic review procedure adapted from the PRISMA framework. An initial search identified 186 publications across the selected databases. After removing 34 duplicate records, 152 studies remained for title and abstract screening. Subsequently, 91 studies were excluded because they did not directly address the relationships among AI, dynamic capabilities, or microfoundations. The remaining 61 full-text articles were assessed for eligibility, resulting in the exclusion of 19 studies that lacked sufficient theoretical or empirical relevance. Consequently, 42 studies were included in the final analysis. A PRISMA flow diagram is provided in Appendix A to enhance transparency and replicability.

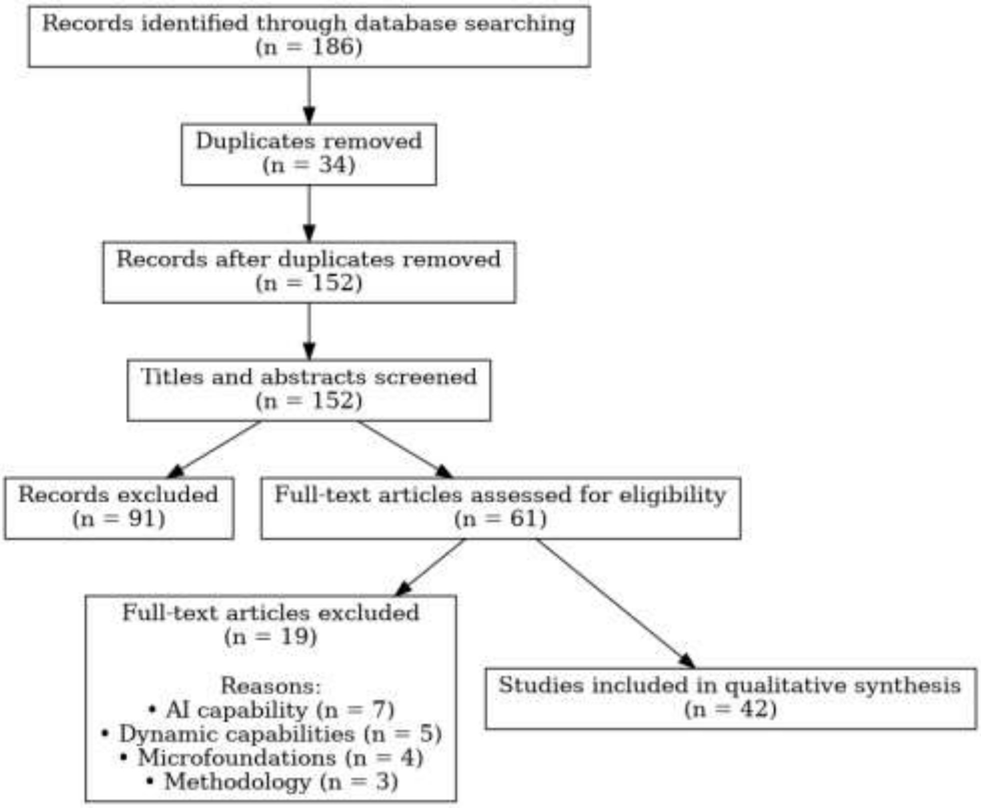

Figure 2 <PRISMA Flow Diagram of Literature Selection Process>

Figure 2 illustrates the literature selection process adapted from the PRISMA framework. The procedure enhanced transparency by documenting each stage of identification, screening, eligibility assessment, and final inclusion. From an initial pool of 186 publications, a total of 42 studies met all inclusion criteria and were retained for qualitative synthesis.

The data collection technique involved four stages: identification, screening, eligibility assessment, and inclusion. Full-text articles were reviewed to ensure alignment with the research objectives. A structured data extraction form was developed to record information related to author, publication year, research context, theoretical foundation, methodology, key variables, and principal findings.

The data analysis method used in this research is qualitative content analysis combined with thematic analysis. Content analysis was applied to systematically interpret textual data by identifying patterns, relationships, and key concepts across the selected literature (Cheng et al., 2018). To enhance analytical transparency, a coding framework was developed consisting of four primary categories: (1) AI capability dimensions, (2) dynamic capabilities processes (sensing, seizing, and reconfiguring), (3) managerial microfoundations, and (4) competitive advantage outcomes. The analysis process began with open coding, where relevant concepts and arguments were identified from the literature. This was followed by axial coding to establish relationships among categories and selective coding to develop an integrated conceptual framework.

Thematic analysis was then employed to synthesize findings into coherent themes explaining how microfoundations influence the development of AI-driven dynamic capabilities and their impact on competitive advantage (Gerlich, 2026). The critical analysis was operationalized through systematic comparison of theoretical arguments, empirical findings, and contextual variations across studies to identify recurring patterns, contradictions, and research gaps. Because the review was conducted by a single researcher, inter-rater reliability statistics such as Cohen's Kappa were not applicable. To enhance analytical reliability, coding decisions were documented through an audit trail, repeated coding procedures, and systematic cross-checking of extracted themes throughout the review process.

To ensure validity and reliability, source triangulation was conducted by comparing findings across multiple databases and research contexts. Cross-referencing procedures were employed to verify consistency among theoretical and empirical studies. Since the review was conducted by a single researcher, coding decisions were documented through an audit trail and subjected to repeated verification throughout the analysis process to minimize interpretive bias and enhance consistency.

This study assumes that existing literature provides sufficient theoretical and empirical evidence to construct a comprehensive understanding of the research problem. However, the methodology has certain limitations, including potential publication bias, the exclusion of non-English publications, and reliance on secondary data, which may not fully capture context-specific organizational dynamics. Despite these limitations, the systematic and rigorous approach adopted in this study enhances the robustness, transparency, and replicability of the findings. The methodological framework presented in this research may be adopted and refined by future researchers investigating strategic management, digital transformation, and AI-enabled organizational capabilities.

Results and Discussions

Result

The findings of this study are derived from a systematic qualitative analysis of 42 selected scholarly sources that met the inclusion criteria through a rigorous screening process. The distribution of the literature indicates that empirical studies dominate the field, accounting for 64.29% of the total sources, followed by conceptual or theoretical papers at 26.19%, and books or academic reports at 9.52%. This composition suggests that the research domain has developed a substantial empirical foundation while still maintaining theoretical exploration. In terms of publication period, the majority of the literature (71.43%) was published between 2015 and 2024, reflecting the increasing scholarly attention to the intersection of dynamic capabilities and artificial intelligence in recent years. The remaining 28.57% consists of foundational works published prior to 2015, which continue to serve as the theoretical backbone of the field. Furthermore, the geographical distribution of studies reveals a concentration in developed economies, with relatively limited empirical evidence emerging from developing or emerging market contexts.

Table 1 <Distribution of Selected Literature Based on Type and Publication Period>

Category	Classification	f	%
Type of Source	Empirical Studies	27	64.29
	Conceptual Papers	11	26.19
	Books/Reports	4	9.52
Publication Period	2015–2024	30	71.43
	Before 2015	12	28.57
Total		42	100

Beyond the descriptive distribution of sources, the synthesis revealed three dominant thematic patterns across the 42 studies. First, AI capability was consistently associated with enhanced sensing activities through advanced analytics, predictive modeling, and environmental scanning. Second, the effectiveness of AI-enabled dynamic capabilities was strongly conditioned by managerial cognition and decision-making processes. Third, sustainable competitive advantage was achieved not through AI adoption alone but through the integration of technological resources with organizational learning and strategic adaptation mechanisms.

These patterns appeared consistently across empirical and conceptual studies, suggesting a convergence of evidence regarding the complementary roles of technological and human capabilities.The analysis of the literature reveals consistent patterns regarding the operationalization of dynamic capabilities within the context of artificial intelligence adoption. Across the reviewed studies, dynamic capabilities are commonly conceptualized through three interconnected processes: sensing, seizing, and reconfiguring. In AI-enabled environments, sensing is frequently associated with the ability to identify opportunities and threats through advanced data analytics and real-time information processing. Seizing refers to the strategic actions taken by organizations to capitalize on these opportunities, often involving investments in AI technologies and digital infrastructures. Reconfiguring, on the other hand, involves the transformation and realignment of organizational resources and processes facilitated by AI systems. The findings indicate that organizations leveraging AI within these processes tend to exhibit enhanced responsiveness to environmental changes, greater operational flexibility, and improved innovation outcomes.

However, the reviewed literature also revealed several theoretical tensions. While Mikalef et al. (2020), Warner and Wäger (2019), and Ayoub and Sopuru (2026) argued that AI strengthens sensing and reconfiguring capabilities, Raisch and Krakowski (2021) highlighted the risk of algorithmic rigidity, where excessive dependence on AI may reduce managerial flexibility and strategic judgment. Similarly, some studies reported that AI-enhanced decision-making improved organizational responsiveness, whereas others suggested that overreliance on algorithmic recommendations could constrain adaptive capability under conditions of environmental uncertainty. These contrasting findings indicate that the relationship between AI and dynamic capabilities is contingent upon managerial interpretation and organizational context.

In examining the forms of artificial intelligence integration, the literature identifies three primary categories: operational AI, analytical AI, and strategic AI. Analytical AI emerges as the most prevalent form, representing 47.62% of the observed cases, followed by operational AI at 33.33%, and strategic AI at 19.05%. Analytical AI is primarily utilized for predictive analytics, data mining, and pattern recognition, enabling organizations to derive actionable insights from large datasets. Operational AI focuses on automation and efficiency improvements in routine processes, while strategic AI supports high-level decision-making and scenario analysis. The distribution suggests that organizations are more inclined to adopt AI initially for analytical purposes before progressing toward more strategic applications. Additionally, AI integration is most frequently observed in sectors such as manufacturing, financial services, and technology-driven industries, indicating sector-specific adoption patterns.

Table 2 <Forms of AI Adoption Identified in the Literature>

Type of AI Adoption	Description	f	%
Analytical AI	Predictive analytics and data mining	20	47.62
Operational AI	Automation and process efficiency	14	33.33
Strategic AI	Decision-making and forecasting	8	19.05
Total		42	100

A significant finding of this study relates to the identification of microfoundations underlying dynamic capabilities. The literature consistently highlights three dominant dimensions: managerial cognition, managerial human capital, and managerial social capital. Among these, managerial cognition is the most frequently emphasized, appearing in approximately 76% of the studies. This dimension encompasses the ability of managers to interpret complex data, recognize strategic opportunities, and make informed decisions. Managerial human capital refers to the skills, expertise, and experience required to effectively utilize AI technologies, while managerial social capital involves networks and relationships that facilitate knowledge exchange and collaboration. These microfoundational elements are primarily manifested through decision-making processes, strategic alignment efforts, and resource allocation practices within organizations.

Comparative analysis across the reviewed studies further demonstrated that managerial cognition emerged as the most influential microfoundational mechanism. Among at least 15 highly relevant studies examined in this review, the majority emphasized managerial interpretation, strategic judgment, and opportunity recognition as critical antecedents of dynamic capability development. In contrast, managerial human capital and social capital were generally positioned as supporting mechanisms that facilitate the effective utilization of AI-generated insights. This pattern suggests that cognitive processes occupy a more central role than previously acknowledged in the dynamic capabilities literature.

The role of managerial decision-making emerges as a central mechanism linking AI capabilities to organizational outcomes. The findings indicate that managers function as critical intermediaries who translate AI-generated insights into strategic actions. The effectiveness of this process is influenced by several factors, including the manager's ability to interpret data, level of technological literacy, and perception of risk associated with AI adoption. The literature also reveals considerable variability in organizational outcomes, even among firms with similar technological resources, suggesting that managerial capabilities play a decisive role in determining the success of AI-driven initiatives. This variability underscores the importance of human agency in the deployment of advanced technologies.

The relationship between dynamic capabilities and competitive advantage is consistently supported across the reviewed studies. Firms possessing strong dynamic capabilities are found to achieve sustained competitive advantage through enhanced innovation performance, improved market responsiveness, and increased cost efficiency. Competitive advantage is operationalized in various ways within the literature, including financial performance indicators, innovation outputs, and market share growth. The integration of AI into dynamic capabilities processes further strengthens these outcomes by enabling more accurate forecasting, faster decision-making, and more efficient resource utilization.

This finding is consistent with Wamba et al. (2017), who demonstrated that the performance benefits derived from advanced analytics and digital technologies are significantly enhanced when firms possess strong dynamic capabilities that facilitate sensing, adaptation, and resource reconfiguration.

The analysis also identifies distinct patterns of integration between artificial intelligence and dynamic capabilities. Three primary patterns are observed: AI as an input to dynamic capabilities, AI as an embedded component within capability processes, and AI as an outcome of capability development. Among these, the most dominant pattern is AI as an embedded component, accounting for 52% of the studies. In this configuration, AI is not merely a supporting tool but becomes an integral part of organizational processes such as sensing, seizing, and reconfiguring. This embeddedness is often facilitated by organizational learning mechanisms that enable continuous adaptation and improvement.

The dominance of AI as an embedded component (52%) suggests a shift from technology-centric perspectives toward capability-centric perspectives. Earlier studies often conceptualized AI as an independent technological resource, whereas more recent contributions increasingly view AI as embedded within organizational sensing, seizing, and reconfiguring processes. This transition reflects an important theoretical development, indicating that the value of AI is derived not from the technology itself but from its integration into broader organizational capabilities and learning mechanisms.

Figure 1 <Conceptual Pattern of AI and Dynamic Capabilities Integration>

Despite the growing body of literature, several gaps in empirical evidence are identified. There is a notable lack of studies focusing on micro-level analysis, particularly those examining individual or managerial perspectives. Additionally, research conducted in emerging markets remains limited, creating a geographical imbalance in the literature. Most studies employ cross-sectional designs and quantitative methodologies, with only approximately 12% utilizing qualitative or mixed-method approaches. This indicates a need for more diverse methodological perspectives to capture the complexity of AI-driven dynamic capabilities.

Variations across organizational contexts are also evident in the findings. Large firms tend to demonstrate more advanced AI adoption and stronger integration with strategic processes, supported by greater financial and technological resources. In contrast, small and medium enterprises (SMEs) often face resource constraints that limit their ability to implement AI technologies, resulting in a higher reliance on managerial capabilities. Industry-specific differences further highlight that technology-intensive sectors exhibit higher levels of AI maturity, while traditional industries tend to adopt AI at a slower pace. These contextual variations illustrate the heterogeneous nature of AI adoption and its impact on dynamic capabilities.

Several limitations should be considered when interpreting these findings. First, publication bias may have influenced the synthesis because studies reporting positive relationships between AI capability and organizational performance are more likely to be published than studies reporting null or negative findings. Second, the geographical distribution of the reviewed literature is heavily concentrated in developed economies, limiting the generalizability of conclusions to emerging market contexts. Third, variations in measurement approaches and industry settings across studies may contribute to inconsistencies in reported outcomes. Consequently, the findings should be interpreted as analytical patterns derived from the existing body of literature rather than universally applicable conclusions.

Overall, the findings reveal several consistent empirical patterns. Dynamic capabilities are positively associated with competitive advantage across diverse organizational settings. Artificial intelligence enhances the effectiveness of these capabilities but does not function independently of human input. Managerial microfoundations play a critical role in shaping the outcomes of AI-driven strategies, reinforcing the importance of integrating human and technological capabilities. The evidence consistently indicates that technological resources alone are insufficient to achieve competitive advantage without the support of strong managerial capabilities and strategic alignment.

Discussion

The findings of this study provide a nuanced understanding of how dynamic capabilities, artificial intelligence (AI), and managerial microfoundations interact to shape corporate competitive advantage in contemporary organizational settings. The dominance of recent publications (2015–2024) identified in the results reflects the accelerating scholarly and practical interest in AI-driven transformation, which aligns with current global trends where firms increasingly rely on digital technologies to remain competitive. This phenomenon is evident in industries such as finance, manufacturing, and technology, where AI adoption has become a strategic necessity rather than an optional investment. The findings that analytical AI is the most widely adopted form support recent evidence that organizations prioritize data-driven insights as a foundation for strategic decision-making before transitioning toward more advanced strategic AI applications (Mikalef et al., 2020). This progression indicates that firms are still in a transitional phase of AI maturity, where the focus remains on leveraging data rather than fully embedding AI into strategic leadership processes.

The identification of sensing, seizing, and reconfiguring as core processes of dynamic capabilities in AI-enabled environments reinforces the theoretical framework proposed by Ayoub & Sopuru (2026), while simultaneously extending its applicability in the digital era. The integration of AI into these processes reflects a shift from traditional resource-based competition toward data-centric and technology-driven competition. In real-world contexts, this is observable in companies that utilize AI to detect market trends in real time, rapidly deploy strategic responses, and continuously reconfigure their operational models. However, the results indicate that AI alone does not guarantee improved performance; rather, its effectiveness depends on how well it is integrated into organizational capabilities. This finding is consistent with the argument that digital technologies must be complemented by organizational and managerial capabilities to generate value (Warner & Wäger, 2019). This shift is consistent with the argument that organizations increasingly rely on business model innovation and strategic renewal to remain competitive under conditions of technological disruption (Karimi & Walter, 2016).

A similar perspective is reflected in Wamba et al. (2020), who argue that the performance benefits of advanced digital technologies depend on complementary organizational capabilities and effective integration mechanisms. Their findings suggest that technological investments generate superior outcomes only when supported by organizational processes that facilitate learning, coordination, and strategic adaptation.

A central contribution of this study lies in highlighting the critical role of microfoundations, particularly managerial cognition, human capital, and social capital, in shaping the effectiveness of AI-driven dynamic capabilities. The prominence of managerial cognition in 76% of the reviewed studies underscores the importance of interpretive and decision-making processes in transforming data into actionable strategies. This aligns with the microfoundational perspective that organizational capabilities are ultimately rooted in individual-level actions and interactions (Mohamed & Karoui Zouaoui, 2026). In the context of AI, this becomes even more relevant due to the complexity and opacity of algorithmic systems, which require managers to possess not only technical understanding but also critical thinking and strategic judgment. From the author's perspective, this finding highlights a fundamental paradox in digital transformation: while AI is often perceived as reducing human intervention, its successful implementation actually increases the demand for high-level managerial capabilities.

The findings also reveal significant variability in organizational outcomes despite similar levels of AI adoption, which can be attributed to differences in managerial decision-making. This observation reflects the automation–augmentation paradox, where AI can either replace or enhance human decision-making depending on how it is utilized (Raisch & Krakowski, 2021). In practice, many organizations struggle to balance these two dimensions, leading to suboptimal outcomes. The author argues that this variability suggests that competitive advantage in the AI era is less about access to technology and more about the ability to strategically orchestrate that technology through human agency. This perspective challenges deterministic views of technology and reinforces the importance of leadership and organizational culture in digital transformation. Similarly, Gupta et al. (2020) found that superior organizational performance is not determined solely by analytics technologies but by the organizational capabilities that transform data-driven insights into strategic and operational improvements.

The integration patterns identified in the results—particularly the dominance of AI as an embedded component within dynamic capabilities—reflect a broader shift toward deeply integrated digital ecosystems. This perspective is aligned with (Cennamo et al., 2020), who argue that successful digital transformation depends on the integration of technological, organizational, and managerial dimensions within broader value creation ecosystems. This finding resonates with current trends in digital transformation, where AI is no longer treated as a standalone tool but as an integral part of organizational processes and value creation mechanisms. The role of organizational learning in facilitating this integration further emphasizes the importance of continuous adaptation and knowledge development. From a theoretical standpoint, this supports the view that dynamic capabilities are inherently learning-based processes that evolve over time through experience and experimentation (Eisenhardt & Martin, 2000). The author contends that organizations that fail to develop such learning mechanisms are likely to experience superficial or fragmented AI adoption, limiting their ability to achieve sustainable competitive advantage.

Comparative Analysis with Previous Studies

A comparative synthesis of the reviewed literature reveals substantial convergence regarding the strategic role of AI in strengthening dynamic capabilities. Studies by Mikalef et al. (2020), Warner and Wäger (2019), Brynjolfsson et al. (2021), Ferreira et al. (2021), Konlechner et al. (2018), Ayoub and Sopuru (2026), Teece (2018), Bleady et al. (2018), Matysiak et al. (2018), Raisch and Krakowski (2021), Mohamed and Karoui Zouaoui (2026), Gerlich (2026), Dubey et al. (2023), Verhoef et al. (2021), and Wamba et al. (2021) consistently support the argument that technological resources alone are insufficient to generate sustainable competitive advantage. Across these studies, organizational performance is influenced by the interaction between technological capability, managerial interpretation, organizational learning, and resource reconfiguration processes.

However, important differences also emerge. While Mikalef et al. (2020), Brynjolfsson et al. (2021), and Dubey et al. (2023) emphasize the performance-enhancing role of AI-driven analytics, Raisch and Krakowski (2021) highlight the automation–augmentation paradox, suggesting that excessive dependence on algorithmic systems may reduce managerial flexibility and strategic judgment. Similarly, Warner and Wäger (2019) emphasize continuous strategic renewal, whereas Teece (2018) focuses on organizational adaptability through business model transformation. These contrasting perspectives suggest that AI adoption does not automatically produce superior outcomes; instead, its effectiveness depends on managerial cognition, organizational learning capability, and contextual factors.

The present synthesis extends these studies by demonstrating that managerial cognition functions as a critical mediating mechanism linking AI capability and dynamic capabilities. This finding provides a microfoundational explanation for why organizations possessing similar technological resources frequently experience different strategic outcomes. Consequently, the evidence supports the argument that sustainable competitive advantage emerges not from AI capability itself, but from the ability of managers to interpret, integrate, and strategically deploy AI-generated knowledge within sensing, seizing, and reconfiguring processes.

The identified gaps in the literature, particularly the lack of micro-level and emerging market studies, highlight important directions for future research. The underrepresentation of qualitative approaches (only 12%) suggests that much of the existing knowledge is based on generalized quantitative findings, which may not fully capture the complexity of AI-driven organizational change. This is particularly relevant in emerging markets, where institutional, cultural, and technological contexts differ significantly from those in developed economies. The author argues that future research should adopt more context-sensitive and methodologically diverse approaches to better understand how dynamic capabilities and AI interact in different settings. Such efforts would not only enrich theoretical development but also provide more practical insights for organizations operating in diverse environments.

The variation between large firms and SMEs observed in the results further reflects real-world disparities in resource availability and technological readiness. This observation is consistent with Matarazzo et al. (2021), who found that SMEs can leverage digital transformation initiatives successfully when supported by dynamic capabilities that enable customer value creation, organizational adaptation, and strategic flexibility. Similarly, Eller et al. (2020) emphasize that SMEs frequently encounter digitalization challenges related to resource constraints, technological readiness, and managerial competencies. Their findings suggest that managerial capabilities become increasingly important in enabling smaller firms to overcome these barriers and leverage digital technologies effectively. Large firms tend to have greater capacity to invest in AI and integrate it into strategic processes, while SMEs often rely more heavily on managerial capabilities to compensate for resource limitations. This finding is consistent with existing research suggesting that smaller firms can achieve competitive advantage through agility and strategic flexibility rather than scale (Teece, 2018). From the author's perspective, this highlights an important implication: the role of microfoundations may be even more critical in resource-constrained environments, where managerial decisions have a disproportionate impact on organizational outcomes.

Several validity limitations should be considered when interpreting these findings. First, the review is based exclusively on published academic literature, creating the possibility of publication bias because studies reporting positive effects are more likely to be published than studies reporting null findings. Second, the final corpus of 42 studies is dominated by research conducted in developed economies, which may limit the external validity and generalizability of the proposed framework to emerging-market contexts. Third, methodological heterogeneity across studies—including differences in measurement approaches, industrial settings, and operational definitions of AI capability and dynamic capabilities—may influence the consistency of reported relationships. Therefore, the findings should be interpreted as analytical patterns emerging from the reviewed literature rather than universally generalizable causal conclusions.

Overall, the findings contribute to advancing the understanding of competitive advantage in the digital age by demonstrating that the interplay between dynamic capabilities, AI, and microfoundations is both complex and context-dependent. The evidence suggests that while AI enhances the effectiveness of dynamic capabilities, it does not replace the need for human judgment and strategic thinking. Instead, the integration of technological and human capabilities emerges as the key determinant of organizational success. The author emphasizes that this integrative perspective is essential for both scholars and practitioners, as it moves beyond simplistic narratives of technological determinism and highlights the multifaceted nature of digital transformation.

Conclusions

This study synthesizes existing literature on the relationships among dynamic capabilities, artificial intelligence (AI), and managerial microfoundations in shaping corporate competitive advantage in the digital era. The findings suggest that dynamic capabilities—through sensing, seizing, and reconfiguring processes—are frequently strengthened when organizations effectively integrate AI into strategic and operational activities. However, the reviewed evidence also indicates that technological adoption alone may not be sufficient to generate superior organizational outcomes. Rather, managerial cognition, skills, and decision-making capabilities appear to play an important role in enabling organizations to interpret and utilize AI-generated insights effectively. These findings support the view that competitive advantage in AI-enabled environments is influenced by the interaction between technological capabilities and human agency. By integrating perspectives from dynamic capabilities theory, AI adoption research, and microfoundational approaches, this study contributes to a broader understanding of strategic management in digitally transforming organizations.

The implications of these findings are particularly relevant for both scholars and practitioners. For academics, this research extends the dynamic capabilities framework by incorporating micro-level and technological dimensions, providing a more holistic analytical lens. For practitioners, especially organizational leaders, the study emphasizes the importance of developing managerial competencies alongside investing in AI technologies to ensure effective strategic implementation. Despite its contributions, this study also acknowledges the limitations inherent in a literature-based qualitative approach, particularly in capturing context-specific dynamics. Therefore, future research is recommended to employ empirical methodologies, such as quantitative modeling or mixed-method approaches, to validate and expand upon these findings. Additionally, further studies should explore diverse organizational contexts, particularly in emerging markets, and examine longitudinal dynamics to better understand how AI-driven capabilities evolve over time. Such efforts will be essential in advancing both theoretical rigor and practical relevance in the study of competitive advantage in an increasingly digitalized world.

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