# AI CAPABILITY IN DYNAMIC CAPABILITIES: A SYSTEMATIC LITERATURE REVIEW USING THE TCCM FRAMEWORK

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**ABSTRACT**

**Research purpose:**

*This study aims to systematically review the literature on artificial intelligence capability in dynamic capabilities research and synthesize the field using the Theory–Context–Characteristics–Methodology (TCCM) framework.*

**Research motivation:**

*Although AI capability has received increasing attention in management, innovation, sustainability, and information systems research, the literature remains fragmented. Prior studies conceptualize AI capability differently, examine diverse contexts, and apply varied methodological approaches. Therefore, a structured review is needed to clarify how AI capability has been theorized and examined within the dynamic capabilities perspective.*

**Research design, approach, and method:**

*This study adopts a systematic literature review approach guided by the PRISMA protocol. A structured search was conducted in Scopus and Web of Science. The initial search identified 179 records. After duplicate removal, screening, and eligibility assessment, 85 articles formed the broader eligible corpus, from which 35 core studies were retained for final TCCM analysis.*

**Main findings:**

*The review shows that Dynamic Capabilities Theory/View is the dominant theoretical lens in this research stream. AI capability is mainly examined in relation to innovation, sustainability, resilience, agility, circular economy practices, and performance outcomes. The findings also reveal that research is concentrated in specific contexts, including SMEs, manufacturing firms, supply chains, logistics, hospitality, and emerging economies. Methodologically, the field is dominated by quantitative and SEM-based studies.*

**Practical/managerial implications:**

*Managers should treat AI capability not merely as a technological investment, but as an organizational capability that supports sensing, seizing, reconfiguring, and strategic adaptation.*

**Keywords:** artificial intelligence capability, dynamic capabilities, systematic literature review

## 1. INTRODUCTION

Artificial Intelligence (AI) fundamentally reshapes modern business, yet simply acquiring AI technologies does not guarantee a sustainable competitive advantage (Fosso Wamba, Queiroz, Pappas, & Sullivan, 2024). Instead, firms must develop "AI Capability" (AIC), defined as the organizational ability to strategically select, orchestrate, and leverage AI-specific resources (Mikalef & Gupta, 2021).

To understand how AIC generates value, researchers increasingly apply Dynamic Capabilities Theory (DCT), which emphasizes a firm's ability to sense, seize, and reconfigure resources in volatile environments (Teece, 2007; Teece, Pisano, & Shuen, 1997). Viewed through this theoretical lens, AIC acts as a critical capability-conversion mechanism that enhances organizational agility (Ameen, Tarba, Cheah, Xia, & Sharma, 2024), drives circular business model innovation (Renfei & Zhongwen, 2026), and fosters information-driven resilience (Wang & Zhang, 2026).

Despite its strategic importance, the literature on AI-enabled dynamic capabilities remains fragmented. Theoretically, scholars disagree on whether AIC is a foundational technological resource, a higher-order dynamic capability, or merely an antecedent to adaptation (Ratanacharoenchai & Jantapoon, 2026). Empirically, evidence is scattered across vastly different contexts, from large B2B manufacturing firms (Li, Xu, Zhang, Liu, & Li, 2025) to informal microenterprises driven by digital bricolage (Kolade, Egbetokun, Owoseni, & Beta, 2024). Consequently, a cohesive understanding of how AIC is developed and embedded across diverse environments is still lacking.

This study conducts a systematic literature review (SLR) to consolidate how AI capability is theorized, contextualized, and operationalized in dynamic capabilitiesliterature (Dhingra & Jaiswal, 2025). We employ the

PRISMA protocol to ensure a rigorous and transparent article selection process (Moher, Liberati, Tetzlaff, & Altman, 2009). Subsequently, the Theory–Context–Characteristics–Methodology (TCCM) framework is applied to systematically structure the analytical synthesis of the selected studies (Dhingra & Jaiswal, 2025).

Following a systematic search in Scopus and Web of Science combining AI and dynamic capability terms, 179 initial records were identified. After removing 73 duplicates, 106 unique records underwent abstract and relevance screening, retaining 104 articles. During the full-text eligibility assessment, 21 records were excluded, resulting in 85 eligible articles. Ultimately, 35 core studies were retained for the final in-depth TCCM analysis, as they provided the most comprehensive and robust evidence regarding the theoretical, contextual, and methodological dimensions of AI-enabled dynamic capabilities.

*Accordingly, this review is guided by the following primary research questions:*

**RQ1.** What is the current research profile of AI capability within dynamic capabilities studies?

**RQ2.** Which theories, contexts, characteristics, and methodologies dominate this research stream?

**RQ3.** How do AI capabilities functionally contribute to dynamic capability mechanisms such as sensing, seizing, and reconfiguring to foster organizational agility, resilience, and sustainable innovation?

**RQ4.** What theoretical, contextual, conceptual, and methodological gaps can be identified to guide future research agendas?

By addressing these questions, this study makes significant contributions to the literature. It clarifies the theoretical boundaries of AI capability, uncovers critical mediating pathways such as green ambidexterity (Chowdhury, Ren, & Dey, 2026) and supply chain resilience (Ratanacharoenchai & Jantapoon, 2026), and offers a robust, structured future research agenda for scholars navigating the nexus of AI and strategic management.

This study makes three salient contributions to the extant literature. First, it provides theoretical clarity by delineating how AI capability is functionally positioned in dynamic capabilities (Mikalef & Gupta, 2021; Teece, Pisano, & Shuen, 1997). Second, it systematically maps the dominant theoretical foundations, empirical contexts, key characteristics, and methodological designs that currently shape this emerging research domain (Dhingra & Jaiswal, 2025). Third, it identifies critical knowledge gaps and proposes a robust future research agenda focused on AI-enabled sensing, seizing, and reconfiguring mechanisms, alongside their subsequent impacts on organizational agility, strategic resilience, and sustainable innovation (Chowdhury, Ren, & Dey, 2026; Wang & Zhang, 2026).

## 2. LITERATURE REVIEW AND THEORETICAL BACKGROUND

### 2.1 Dynamic Capabilities Theory

DCT was developed to explain how firms build, integrate, and reconfigure internal and external competences to address rapidly changing environments (Teece, Pisano, & Shuen, 1997). The seminal dynamic capabilities perspective argues that competitive advantage in turbulent markets depends not only on the possession of valuable resources but also on the firm's ability to renew and redeploy those resources when technologies, markets, and institutional conditions change (Eisenhardt & Martin, 2000). Within this perspective, dynamic capabilities are commonly understood through the microfoundations of sensing, seizing, and transforming or reconfiguring (Teece, 2007). Sensing refers to the identification and assessment of opportunities and threats in the external environment (Teece, 2021). Seizing involves mobilizing resources to capture identified opportunities and generate business value (Teece, 2014). Transforming refers to the continuous renewal and realignment of organizational assets and structures to maintain adaptability (Teece, 2007).

The relevance of DCT has significantly increased in the digital era because firms now face more frequent technological discontinuities, faster information flows, and stronger pressure to adapt their resource bases (Chowdhury, Ren, & Dey, 2026). In this context, dynamic capabilities provide a robust theoretical lens for explaining how organizations use digital and AI-related capabilities to support innovation, resilience, agility, sustainability, and strategic renewal (Warner & Wäger, 2019). The 35-study corpus reviewed in this paper demonstrates that DCT is the dominant theoretical foundation in research concerning AI capability and dynamic organizational adaptation (Lu, Fan, Troise, & Bresciani, 2026).

DCT is particularly suitable for this review because AI capability is rarely valuable as a stand-alone technological asset (Mikalef & Gupta, 2021). Instead, AI capability becomes strategically meaningful when it is embedded in organizational processes that enable firms to sense environmental changes, seize emerging opportunities, and reconfigure resources, routines, and business models (Pi, Ma, & Wang, 2026). This interpretation aligns with recent empirical research showing that AI-enabled capabilities operate as higher-order dynamic mechanisms that support organizational agility, innovation, resilience, circular business model innovation, and sustainable performance (Ameen et al., 2024; Ratanacharoenchai & Jantapoon, 2026; Sjödin, Parida, & Kohtamäki, 2023; Wang & Zhang, 2026).

### 2.2 Conceptualizing AI Capability

AI capability (AIC) is conceptualized not merely as the adoption of an algorithm, but as a firm's complex ability to select, orchestrate, and leverage AI-specific resources to achieve strategic organizational goals (Mikalef & Gupta, 2021; Pi, Ma, & Wang, 2026). Grounded in the resource-based view (RBV), AIC operates as a multidimensional construct built from three core components: tangible resources (such as digital infrastructure and data architecture), human resources (including technical AI expertise and business managerial skills), and intangible organizational resources (such as interdepartmental coordination, risk proclivity, and organizational change capacity) (Lu, Fan, Troise, & Bresciani, 2026; Mariani & Mancini, 2025; Mikalef & Gupta, 2021).

Furthermore, through the lens of dynamic capabilities, AIC manifests hierarchically across three progressive levels of sophistication: perceptive, predictive, and prescriptive capacities (Renfei et al., 2026; Sjödin, Parida, & Kohtamäki, 2023). Perceptive capacities support the real-time identification and interpretation of data patterns; predictive capacities utilize machine learning to anticipate future trends and events; and prescriptive capacities optimize strategic actions by providing automated decision recommendations (Renfei et al., 2026; Sjödin, Parida, & Kohtamäki, 2023).

This hierarchical and composite view is theoretically crucial because it demonstrates that AIC is not a single uniform construct. The 35-study corpus reflects this configurational diversity by examining specialized manifestations of AI capabilities tailored to specific contexts, including generative AI capabilities (Li et al., 2025), situated AI capabilities (Pi, Ma, & Wang, 2026), AI assimilation (Chowdhury, Ren, & Dey, 2026), organizational sustainable AI capabilities (Qalati & Siddiqui, 2026), AI workforce integration (Chatjuthamard et al., 2026), and AI-integrated customer relationship management (Chatterjee, Mikalef, Khorana, & Kizgin, 2022).

### 2.3. AI Capability as an Enhancer of Dynamic Capabilities

The intersection of AI and Dynamic Capabilities Theory (DCT) indicates that AI capability should not strictly be treated as an independent algorithmic capability. A more analytically precise interpretation is that AI functions as a powerful capability enhancer that transforms traditional dynamic processes (Ratanacharoenchai & Jantapoon, 2026). Specifically, AI exponentially strengthens the speed, scale, and informational quality of organizational sensing, seizing, and reconfiguring activities, while these processes remain fundamentally embedded in human judgment and strategic managerial frameworks (Ratanacharoenchai & Jantapoon, 2026; Wang & Zhang, 2026).

Through the lens of DCT microfoundations, AI capability operates across three primary dimensions. In relation to sensing, AI algorithms—capable of handling massive and complex datasets—improve a firm's ability to scan environments and detect weak signals, customer preferences, and sustainability risks that surpass human cognitive limits (Cassânego et al., 2025; Ratanacharoenchai & Jantapoon, 2026). Regarding seizing, AI enables faster and more informed resource allocation by evaluating thousands of strategic alternatives simultaneously. Empirical evidence confirms that coupling AI capability with strategic agility significantly enhances new product and service creativity by allowing firms to rapidly respond to market volatility (Ameen et al., 2024). In relation to reconfiguring, AI capabilities support continuous organizational renewal by facilitating the redesign of routines and structures. For instance, AI empowers the transformation of traditional operations into circular business model innovations by optimizing value discovery and resource realization in digital servitization contexts (Sjödin, Parida, & Kohtamäki, 2023).

Consequently, this review positions AI capability as a capability-conversion mechanism rather than a direct determinant of performance. AI investments do not automatically produce competitive advantage, innovation, or sustainability; instead, their value is unlocked only when firms successfully embed algorithmic intelligence into human-centric dynamic capabilities (Javed et al., 2026). This interpretation is highly consistent with the 35-study corpus, which demonstrates that AI capabilities successfully translate into strategic outcomes primarily through mediating organizational enablers—such as green ambidexterity, strategic resilience, and business model transformation (Chowdhury, Ren, & Dey, 2026; Le et al., 2026; Wang & Zhang, 2026).

## 3. METHODOLOGY

This study conducts a systematic literature review (SLR) to synthesize the fragmented research on AI capabilities in dynamic capabilities (Dhingra & Jaiswal, 2025). To ensure methodological rigor and transparency, we integrate two well-established approaches: the PRISMA protocol governs the systematic identification and selection of articles (Moher, Liberati, Tetzlaff, & Altman, 2009), while the TCCM (Theory–Context–Characteristics–Methodology) framework is applied to structure and analyze the selected literature (Paul & Rosado-Serrano, 2019).

### 3.1 Keywords search

The literature search was conducted using Scopus and Web of Science, as these databases provide broad coverage of peer-reviewed research in business, management, strategy, innovation, information systems, sustainability, supply

chain, and organizational studies. The search strategy was designed to capture studies located at the intersection of AI capability and dynamic capabilities.

**Table 1.** Search keyword structure

| Keyword block | Search terms | Purpose |
|---|---|---|
| AI capability block | "artificial intelligence capabilit*"; "AI capabilit*"; "AI-enabled capabilit*"; "AI-based capabilit*"; "artificial intelligence competenc*" | To identify studies examining AI as an organizational capability or competence |
| Dynamic capabilities block | "dynamic capabilit*" | To identify studies connected to Dynamic Capabilities Theory/View or related capability-based logic |
| Boolean operator | AND | To retain only studies located at the intersection of AI capability and dynamic capabilities |

This keyword design was deliberately focused. The first keyword block captures AI-related capability and competence constructs, including AI capability, AI capability, AI-enabled capability, AI-based capability, and AI competence. The second keyword block captures the dynamic capabilities domain through the wildcard expression "dynamic capabilit*", which retrieves both "dynamic capability" and "dynamic capabilities."

The search strategy therefore excluded broader AI terms such as "AI adoption," "AI implementation," or "digital transformation" unless these studies also contained AI capability or AI competence terminology linked to dynamic capabilities. This decision strengthens conceptual precision by ensuring that the final corpus remains focused on capability-based AI research rather than general AI adoption literature.

**3.2 Identification**

In the identification stage, the search was conducted in Scopus and Web of Science using the keyword structure described above. The initial search identified 179 records, consisting of 86 records from Scopus and 93 records from Web of Science.

All records were exported into a consolidated dataset. At this stage, no record was excluded based on research design, theory, country, industry, or methodology. This ensured that the review captured the widest possible set of articles linking AI capability or AI competence with dynamic capabilities.

**3.3 Screening**

During the screening stage, duplicate records were removed and the remaining records were screened based on title, abstract, keywords, and source information. From the initial 179 records, 73 duplicate records were removed. This resulted in 106 unique records for further screening.

The screening process focused on whether each record explicitly addressed AI capability, AI-enabled capability, AI-based capability, AI capability, AI competence, or a closely related AI capability construct. The screening also checked whether the record contained a meaningful connection to dynamic capabilities.

After publication-year and relevance screening, 104 records were retained for eligibility assessment. Records were excluded at this stage if they only mentioned AI as a general technology without discussing AI capability or AI competence, or if they did not relate to dynamic capabilities in any meaningful way.

**3.4 Eligibility**

The eligibility stage assessed whether each screened article substantively fitted the purpose of the review. The assessment was based on title, abstract, keywords, journal/source information, theoretical framing, variables, methodology, and research contribution.

*The inclusion criteria were as follows:*

- The study explicitly examined artificial intelligence capability, AI capability, AI-enabled capability, AI-based capability, artificial intelligence competence, or a closely related AI capability construct.
- The study explicitly connected the AI capability construct to dynamic capability or dynamic capabilities.
- The study provided sufficient information for TCCM coding, including theory, context, variables, and methodology.
- The study was relevant to business, management, strategy, innovation, sustainability, information systems, marketing, supply chain, logistics, entrepreneurship, hospitality, or organizational performance.
- The study was published in a peer-reviewed academic outlet or equivalent scholarly source.

*The exclusion criteria were as follows:*

- Studies that discussed AI adoption, AI implementation, or digital transformation without a clear AI capability or AI competence construct.

- Studies that mentioned dynamic capabilities only superficially without connecting them to AI capability.
- Editorials, commentaries, non-scholarly documents, or records without sufficient methodological or conceptual information.
- Studies lacking enough information for TCCM coding.
- Studies outside the substantive focus of AI capability in dynamic capabilities.

Following eligibility assessment, 21 records were excluded. This produced a broader eligible corpus of 85 articles. From this broader corpus, a focused set of 35 core studies was selected for final TCCM analysis. These 35 studies were retained because they provided the clearest and most complete information on theory, context, characteristics, methodology, and research contribution.

**Inclusion**

The final inclusion stage resulted in 35 studies retained for in-depth TCCM synthesis. These studies formed the final analytical corpus of the review. The included studies examine AI capability in relation to generative AI capability, green AI capability, sustainable AI capability, AI-enabled dynamic capabilities, AI-based organizational capabilities, strategic agility, organizational resilience, supply chain resilience, servitization, business model transformation, circular economy, innovation performance, export performance, hotel performance, cyber supply chain risk management, and sustainable competitive performance.

**Table 2.** PRISMA flow summary

| PRISMA Stage | Description of the Process | Number of Records (n) |
|---|---|---|
| 1. Identification | Records identified through Scopus database | 86 |
| | Records identified through Web of Science database | 93 |
| | Total records identified before duplicate removal | 179 |
| 2. Screening | Duplicate records removed | (73) |
| | Unique records remaining after duplicate removal | 106 |
| | Records retained after publication-year and title/abstract screening | 104 |
| 3. Eligibility | Records excluded after full-text eligibility assessment | (21) |
| | Articles eligible for the broader review corpus | 83 |
| 4. Inclusion | Core articles included for final TCCM analysis | 35 |

## 4. RESULTS AND DISCUSSION

### 4.1 Theory

The theory dimension identifies the theoretical foundations used to explain the relationship between AI capability and dynamic capabilities. The coding shows that Dynamic Capabilities Theory/View is the dominant theoretical foundation.

**Table 3**. Theoretical foundations

| Theory category | Number | Proposed Authors |
|---|---|---|
| DCT / Dynamic Capabilities View / dynamic capability-related perspective | 27 | Li et al. (2025); Zahoor et al. (2025); Liang and Sun (2026); Abou-Foul et al. (2023); Ameen et al. (2024); Wang et al. (2026) |
| Resource-Based View / resource-based logic | 7 | Dubey et al. (2020); Duzgun and Nguyen (2026); Cassânego et al. (2025); Ratanacharoenchai and Jantapoon (2026); Mariani and Mancini (2025) |
| Knowledge-based / learning-related lens | 4 | Pi et al. (2026); Kumar et al. (2025); Lu et al. (2026); al-Hakimi et al. (2025) |
| Institutional, stakeholder, legal, or ethical perspectives | 2 | Duzgun and Nguyen (2026); Huy (2025) |
| Resource orchestration theory | 1 | Tajeddini et al. (2026) |
| Bricolage theory | 1 | Kolade et al. (2024) |
| Fit theory / technology acceptance | 1 | Chatterjee et al. (2022) |
| Firm life cycle theory | 1 | Chatjuthamard et al. (2026) |
| Paradox theory | 1 | Qalati and Siddiqui (2026) |
| Sustainability perspective | 1 | Renfei et al. (2026) |

The corpus is strongly anchored in Dynamic Capabilities Theory/View, appearing in 27 of the 35 studies. This indicates that AI capability is mainly theorized as a mechanism through which firms sense opportunities, seize strategic options, adapt to environmental turbulence, and reconfigure resources. Resource-Based View appears in 7 studies, suggesting that AI capability is also treated as a strategic resource bundle. Knowledge-based and learning-related perspectives appear in 4 studies, showing that knowledge orchestration, organizational learning, and green knowledge management are important complementary mechanisms.

Future research must clarify the precise theoretical positioning of AI capability in dynamic capabilitiesframework, as current literature exhibits significant conceptual ambiguity regarding its fundamental nature (Ratanacharoenchai & Jantapoon, 2026). Specifically, scholars need to rigorously determine whether AI capability functions merely as a foundational technological resource, an ordinary capability, a higher-order dynamic capability, or strictly as an antecedent that stimulates human-driven dynamic capabilities (Mikalef & Gupta, 2021; Ratanacharoenchai & Jantapoon, 2026). Elucidating these theoretical boundaries will help researchers understand whether AI directly reconfigures firm resources or acts as a supplementary enhancer for traditional organizational adaptation processes (Ratanacharoenchai & Jantapoon, 2026; Teece, 2007).

To advance the theoretical frontier, future studies should first address the theoretical ambiguity surrounding AI capability, as recent literature shows that this construct is not conceptualized consistently across various research streams (Ratanacharoenchai & Jantapoon, 2026). Some studies treat AI capability as a strategic technological resource, while others position it as an antecedent, component, or enhancer of dynamic capabilities (Ratanacharoenchai & Jantapoon, 2026). This theoretical inconsistency is highly visible across studies examining generative AI capabilities, situated AI capabilities, sustainable AI capabilities, and AI-based sensing–seizing–reconfiguring mechanisms (Ciceri et al., 2025; Li et al., 2025; Pi et al., 2026; Qalati & Siddiqui, 2026). Consequently, future studies must distinguish more clearly between AI resources, AI capability, AI-enabled dynamic capabilities, and AI-driven strategic outcomes (Mikalef & Gupta, 2021; Ratanacharoenchai & Jantapoon, 2026). AI resources inherently include data, algorithms, infrastructure, and technical expertise, whereas AI capability refers to the organizational ability to coordinate and deploy these specific resources for strategic purposes (Mikalef & Gupta, 2021; Ratanacharoenchai & Jantapoon, 2026). Thus, AI-enabled dynamic capabilities should be empirically examined as higher-order mechanisms through which firms use AI to sense environmental changes, seize opportunities, and reconfigure organizational resources (Abou-Foul et al., 2023; Liu & Xin, 2026; Ratanacharoenchai & Jantapoon, 2026).

Finally, future research should integrate DCT with complementary theoretical lenses, such as the resource-based view (RBV), knowledge-based view (KBV), resource orchestration theory, paradox theory, and institutional theory (Alsharaideh et al., 2026; Duzgun & Nguyen, 2026; Qalati & Siddiqui, 2026; Tajeddini et al., 2026). This cross-theoretical integration is imperative because the reviewed studies demonstrate that AI capability does not operate solely as a technological construct; rather, its effectiveness is profoundly shaped by knowledge management, managerial cognition, absorptive capacity, stakeholder integration, institutional pressures, and legal–ethical considerations (Abou-Foul et al., 2023; Duzgun & Nguyen, 2026; Huy, 2025; Kumar et al., 2025; Qalati & Siddiqui, 2026; Renfei & Zhongwen, 2026).

**4.2 Context**

The context dimension captures the geographical, sectoral, and organizational

**Table 4.** Geographic context

| Geographic context | Number | Proposed Authors |
|---|---|---|
| China / China-related sample | 8 | Li et al. (2025); Liang and Sun (2026); Pi et al. (2026); Liu and Xin (2026) |
| Vietnam | 4 | Duzgun and Nguyen (2026); Le et al. (2026); Duong (2026); Huy (2025) |
| Malaysia | 3 | Tajeddini et al. (2026); al-Hakimi et al. (2025); Naz et al. (2024) |
| Europe / North America / cross-regional developed-market sample | 5 | Abou-Foul et al. (2023); Wang and Zhang (2026); Qalati and Siddiqui (2026); Lu et al. (2026); Mariani and Mancini (2025) |
| Global sample | 2 | Dubey et al. (2020); Cassânego et al. (2025) |
| United Kingdom | 1 | Chowdhury et al. (2026) |
| Thailand | 1 | Ratanacharoenchai and Jantapoon (2026) |
| Pakistan | 1 | Javed et al. (2026) |
| Country/region not clearly stated in the Excel context column | 11 | Zahoor et al. (2025); Kumar et al. (2025); Al Halbusi et al. (2025); Ameen et al. (2024); Wang et al. (2026) |

The evidence is concentrated in Asian and emerging-economy contexts, especially China, Vietnam, and Malaysia. China-related samples appear in 8 studies, while Vietnam appears in 4 studies. Eleven studies do not clearly state the country or region in the Excel context column; therefore, they should not be assigned to any specific geography without checking the original papers.

**Table 5.** Sectoral and organizational context

| Sectoral / organizational context | Number | Proposed Authors |
|---|---|---|
| SMEs / microenterprises / startups | 12 | Pi et al. (2026); Wang and Zhang (2026); Duzgun and Nguyen (2026); Kolade et al. (2024); Kumar et al. (2024) |
| Manufacturing / production-related firms | 8 | Zahoor et al. (2025); Abou-Foul et al. (2023); Renfei et al. (2026); Dubey et al. (2020); Javed et al. (2026) |
| Manager / employee / accountant respondent group | 5 | Al Halbusi et al. (2025); Chowdhury et al. (2026); Qalati and Siddiqui (2026); Ciceri et al. (2025) |
| Supply chain / logistics | 3 | Chowdhury et al. (2026); Duzgun and Nguyen (2026); Ciceri et al. (2025) |
| B2B / B2C firms | 3 | Li et al. (2025); Kumar et al. (2025); Chatterjee et al. (2022) |
| Listed / archival firm-level datasets | 3 | Liang and Sun (2026); Liu and Xin (2026); Cassânego et al. (2025) |
| Hospitality / hotel / tourism | 2 | Tajeddini et al. (2026); Naz et al. (2024) |
| High-tech enterprises / high-tech startups | 2 | Le et al. (2026); Wang et al. (2026) |
| Public sector | 1 | Zahoor et al. (2025) |
| Project-based organizations | 1 | Mariani and Mancini (2025) |
| Accounting / cyber forensic accounting | 1 | Huy (2025) |

SMEs, microenterprises, and startups form the largest organizational context, appearing in 12 studies. Manufacturing or production-related firms appear in 8 studies. The corpus therefore emphasizes firms that face resource constraints, digital transformation pressure, operational uncertainty, and sustainability challenges.

Future research must expand the contextual scope of AI capability research, as the current corpus is predominantly concentrated in emerging Asian markets—such as China, Vietnam, Malaysia, Thailand, and Pakistan—along with selected European and global samples (Chowdhury et al., 2026; Duong, 2026; Duzgun & Nguyen, 2026; Li et al., 2025). Furthermore, existing empirical evidence exhibits a strong sectoral focus on small and medium-sized enterprises (SMEs), startups, microenterprises, manufacturing firms, logistics, supply chain operations, hospitality, and high-tech firms (Al-Hakimi et al., 2025; Duzgun & Nguyen, 2026; Li et al., 2025; Naz et al., 2024). While this concentration provides valuable foundational evidence regarding AI integration, it inherently limits the generalizability of the findings across diverse institutional, cultural, and sectoral environments (Chowdhury et al., 2026; Duong, 2026; Renfei et al., 2026).

Consequently, future studies should empirically examine AI capability in underexplored organizational settings, including healthcare, education, agriculture, financial services, public administration, creative industries, and large established firms (Amankwah-Amoah et al., 2024; Daly et al., 2025; Damoah et al., 2021; Qatawneh, 2024; Shakeripour & Ronaghi, 2024; Wirtz et al., 2018). Several scholars explicitly call for broader contextual testing across various industries, countries, and institutional environments to validate existing frameworks (Chowdhury et al., 2026; Le et al., 2026; Renfei et al., 2026; Wang & Zhang, 2026). This contextual expansion is theoretically critical because AI capability and its strategic outcomes may operate differently under varying levels of technological turbulence, regulatory pressure, resource constraints, and digital infrastructure maturity (Chowdhury et al., 2026; Le et al., 2026; Wang & Zhang, 2026).

Finally, future research should transcend macro-level firm analyses to investigate the micro-foundations of AI-enabled dynamic capabilities (Al Halbusi et al., 2025; Chatjuthamard et al., 2026). Although the reviewed corpus includes some attention to managers, accountants, general employees, and supply chain managers (Chowdhury et al., 2026; Huy, 2025; Javed et al., 2026), individual-level and team-level conceptualizations of AI capability remain significantly underdeveloped (Chowdhury et al., 2022). Therefore, future studies must rigorously examine employee AI readiness, managerial AI cognition, human–AI collaboration, team learning, digital leadership, and employee resilience as critical micro-foundational mechanisms (Al Halbusi et al., 2025; Chatjuthamard et al., 2026; Javed et al., 2026; Renfei & Zhongwen, 2026; Simón et al., 2024). Exploring these micro-level dynamics will provide a more

granular understanding of how human-centric elements interact with algorithmic resources to sustain organizational agility and competitive advantage (Chowdhury et al., 2022; Javed et al., 2026).

**4.3 Characteristics**

The characteristics dimension examines how the reviewed studies conceptualize the main variables, mechanisms, boundary conditions, and outcomes related to AI capability. Across the 35 core studies, AI-related constructs appear in all articles, confirming that AI capability is the central construct of this review. However, the role of AI capability differs across studies. In some articles, AI capability is treated as an antecedent of innovation, sustainability, resilience, or performance, while in others it functions as a mediator, moderator, or capability-enhancing mechanism.

**Table 6.** Summary of characteristics in the reviewed studies

| Characteristics category | Number | Proposed Authors |
|---|---|---|
| Studies including AI-related constructs | 35 | Li et al. (2025); Chowdhury et al. (2026); Qalati and Siddiqui (2026); Chatterjee et al. (2024) |
| AI capability used mainly as an antecedent or strategic driver | 26 | Li et al. (2025); Kumar et al. (2025a); Wang and Zhang (2026); Ratanacharoenchai and Jantapoon (2026) |
| Studies including mediating mechanisms | 30 | Abou-Foul et al. (2023); Liu and Xin (2026); Le et al. (2026); Lu et al. (2026) |
| Studies including moderating variables | 19 | Li et al. (2025); Ameen et al. (2024); Chowdhury et al. (2026); Kumar et al. (2025b) |
| Performance, value, competitive advantage, or success outcomes | 22 | Li et al. (2025); Mariani et al. (2025); Naz et al. (2024); Wang et al. (2026) |
| Innovation, creativity, transformation, servitization, or bricolage outcomes/mechanisms | 20 | Abou-Foul et al. (2023); Ameen et al. (2024); Duong (2026); Pi et al. (2026) |
| Sustainability, green, circular economy, or environmental outcomes/mechanisms | 16 | Zahoor et al. (2025); Renfei and Zhongwen (2026a); Chowdhury et al. (2026); Qalati and Siddiqui (2026) |
| Resilience, agility, or strategic adaptation mechanisms | 10 | Wang and Zhang (2026); Ratanacharoenchai and Jantapoon (2026); Javed (2026); Lu et al. (2026) |
| Governance, cyber risk, institutional, stakeholder, legal, or ethical constructs | 7 | Ciceri et al. (2026); Huy and Phuc (2025); Duzgun and Nguyen (2026); Chowdhury et al. (2026) |

The synthesized findings reveal that current literature rarely examines artificial intelligence (AI) capability as a simple, direct predictor of organizational performance. Instead, scholars increasingly unpack the "black box" of value creation by introducing complex mediating mechanisms. The vast majority of the 37 reviewed studies incorporate at least one intermediate variable, demonstrating that AI capability generates value primarily through organizational transformation mechanisms rather than direct technological effects (Wang & Zhang, 2026). Specifically, the literature highlights critical mediators such as service innovation (Li et al., 2025), green technology innovation (Kumar et al., 2025), green ambidexterity (Chowdhury, Ren, & Dey, 2026; Duong, 2026), strategic resilience (Wang & Zhang, 2026), and business model transformation (Le et al., 2026). Furthermore, AI capabilities are channeled through micro-foundational mechanisms such as knowledge recombination, R&D efficiency (Liu & Xin, 2026), organizational agility (Mariani & Mancini, 2025), employee resilience (Javed, 2026), and environmental strategy (AlKoliby et al., 2025). This pattern robustly confirms that AI technologies must be embedded into dynamic operational and human routines to yield tangible outcomes.

The strategic impact of AI capabilities is highly conditional rather than universal, as evidenced by the widespread integration of boundary conditions across the corpus. Over half of the reviewed studies employ at least one moderating variable to explain how organizational, environmental, and institutional contexts amplify or constrain the effectiveness of AI deployment. The most prominent boundary conditions include environmental dynamism (Li et al., 2025), absorptive capacity (Abou-Foul, Ruiz-Alba, & López-Tenorio, 2023), green knowledge management (Kumar et al., 2025), cybersecurity awareness (Chowdhury, Ren, & Dey, 2026), and digital literacy (Ali et al., 2025). Additionally, structural and macro-level moderators such as technological turbulence (Le et al., 2026), firm size (Ratanacharoenchai & Jantapoon, 2026), government institutional support (Ameen, Tarba, Cheah, Xia, & Sharma, 2024), and managerial cognition (Renfei & Zhongwen, 2026) significantly dictate whether AI capabilities translate into competitive success or fail due to structural inertia.

The Outcomes include studies frequently link AI capability to overarching competitive advantage (Li et al., 2025), operational performance (Ali et al., 2025), sustainable competitive performance (Renfei et al., 2026), and specialized metrics such as export and hotel performance. AI acts as a catalyst for multifaceted innovation, encompassing service innovation (Li et al., 2025), disruptive innovation (Al Halbusi, Popa, Soto-Acosta, & Alshallaqi, 2025), frugal innovation (Alsharaideh et al., 2026), circular business model innovation (Renfei & Zhongwen, 2026), and enhanced product creativity (Ameen, Tarba, Cheah, Xia, & Sharma, 2024). The literature heavily emphasizes ecological and social returns, linking AI to circular economy practices (Zahoor et al., 2025), corporate sustainability performance (Renfei et al., 2026), environmental sustainability (Kumar et al., 2025), and sustainable innovation (Qalati & Siddiqui, 2026). Reflecting the need for survival in volatile markets, recent studies increasingly highlight strategic resilience (Wang & Zhang, 2026), supply chain resilience (Ratanacharoenchai & Jantapoon, 2026), organizational agility (Lu, Fan, Troise, & Bresciani, 2026), and agile strategic adaptation as primary outcomes of AI-enabled dynamic capabilities.

Regarding capability characteristics, the rapid evolution of AI requires researchers to investigate generative AI capabilities, which present distinct operational affordances compared to traditional predictive analytics (Cillo & Rubera, 2024; Li et al., 2025). Furthermore, to address the "AI sustainability paradox," future agendas must focus on responsible AI capabilities and ethical governance structures that mitigate algorithmic bias, ensure data privacy, and minimize severe ecological impacts (Mancuso et al., 2025; Papagiannidis et al., 2023; Qalati & Siddiqui, 2026). Researchers should also thoroughly explore explainable AI (XAI) and human–AI collaboration to understand how transparency and human-machine teaming foster trust and enhance strategic decision-making in volatile environments (Barredo Arrieta et al., 2020; Simón et al., 2024).

In addition, future research should develop richer construct models that explain how AI capabilities are converted into diverse organizational outcomes, including competitive advantage, servitization, circular economy practices, supply chain resilience, and sustainable competitive performance (Abou-Foul et al., 2023; Ameen et al., 2024; Chowdhury et al., 2026; Kumar et al., 2025). Although current models are already mediation-rich, future studies should examine more deeply how specific intermediate mechanisms—such as knowledge recombination (Liu & Xin, 2026), green ambidexterity innovation (Chowdhury et al., 2026; Duong, 2026), employee resilience (Javed et al., 2026), strategic agility (Ameen et al., 2024; Wang & Zhang, 2026), and business model transformation (Le et al., 2026)—dynamically convert AI capabilities into sustainable performance.

Finally, future research must extend the boundary-condition logic of the field by examining complex moderators such as cybersecurity awareness, legal–ethical governance, AI maturity, and environmental dynamism that shape the effectiveness of AI capabilities (Chatjuthamard et al., 2026; Chowdhury et al., 2026; Huy, 2025; Li et al., 2025). A particularly critical future direction is exploring the "dark side" of AI capability, which remains significantly less developed than its positive performance outcomes (Ratanacharoenchai & Jantapoon, 2026). Scholars should systematically investigate algorithmic bias, job displacement, massive AI energy consumption, cybersecurity vulnerabilities, and liability issues as detrimental conditions that may weaken, constrain, or redirect the strategic value of AI integration (Ciceri et al., 2025; Huy, 2025; Qalati & Siddiqui, 2026; Ratanacharoenchai & Jantapoon, 2026).

### 4.4 Methodology

The methodology dimension summarizes research designs and analytical methods.

**Table 7.** Overall research design

| Research design | Number | Proposed Authors |
|---|---|---|
| Quantitative | 30 | Li et al. (2025); Renfei et al. (2026); Liu and Xin (2026); Ameen et al. (2024); Wang et al. (2026) |
| Mixed methods | 2 | Wang and Zhang (2026); Duzgun and Nguyen (2026) |
| Qualitative | 2 | Pi et al. (2026); Ciceri et al. (2025) |
| Quantitative / conceptual framework | 1 | Kolade et al. (2024) |

Quantitative research dominates the corpus, accounting for 30 of the 35 studies. Mixed-method and qualitative studies remain limited. This is important because dynamic capabilities are processual and time-sensitive, but the current evidence base is still mainly model-testing oriented.

**Table 8.** Main analytical techniques

| Analytical technique | Number | Proposed Authors |
|---|---|---|
| SEM-related methods, including SEM and PLS-SEM | 25 | Abou-Foul et al. (2023); Dubey et al. (2020); Ameen et al. (2024); Chatterjee et al. (2022) |
| PLS-SEM | 23 | Li et al. (2025); Zahoor et al. (2025); Chowdhury et al. (2026); Naz et al. (2024) |
| Panel / archival / IV / matching-related methods | 4 | Liang and Sun (2026); Liu and Xin (2026); Cassânego et al. (2025); Chatjuthamard et al. (2026) |
| Interview / case-study / thematic-analysis component | 4 | Pi et al. (2026); Wang and Zhang (2026); Duzgun and Nguyen (2026); Ciceri et al. (2025) |
| fsQCA | 2 | Abou-Foul et al. (2023); Wang and Zhang (2026) |
| Longitudinal survey design | 2 | Chowdhury et al. (2026); Le et al. (2026) |
| Polynomial or hierarchical regression | 2 | Duong (2026); Wang et al. (2026) |
| Scale development / validation using EFA and CFA | 1 | Qalati and Siddiqui (2026) |

SEM-related methods are the most common analytical approach, appearing in 25 studies. PLS-SEM alone appears in 23 studies. Only 2 studies explicitly use longitudinal survey designs, and only 4 studies contain interview, case-study, or thematic-analysis components. This indicates a methodological imbalance: the field is strong in cross-sectional model testing but weaker in process-based, longitudinal, and qualitative explanations of how AI capability develops over time.

The prevailing reliance on cross-sectional quantitative designs restricts the ability to establish definitive causal mechanisms and limits a process-based understanding of how AI capabilities (AIC) are developed, embedded, and reconfigured over time (Ali et al., 2025; Ratanacharoenchai & Jantapoon, 2026). Therefore, future studies must increasingly adopt longitudinal or multi-wave panel designs to accurately capture the temporal evolution, delayed effects, and co-evolutionary dynamics between AI capabilities and organizational transformation (Chowdhury et al., 2026; Le et al., 2026; Wang & Zhang, 2026). To strengthen empirical robustness, researchers should integrate survey data with objective indicators and archival datasets, which are particularly effective for investigating long-term strategic adaptation, AI workforce maturity, and firm-level innovation (Cassânego et al., 2025; Chatjuthamard et al., 2026; Liang & Sun, 2026; Liu & Xin, 2026). Moreover, incorporating mixed-method approaches and in-depth qualitative case studies is essential to provide richer, processual insights into how ventures orchestrate knowledge and develop situated AI capabilities during complex digital transformations (Ciceri et al., 2025; Duzgun & Nguyen, 2026; Pi et al., 2026). Finally, future research should embrace configurational methods like fuzzy-set Qualitative Comparative Analysis (fsQCA) to uncover asymmetric, equifinal pathways to sustainability, alongside multi-level modeling to connect human-centered micro-foundations—such as employee resilience, team learning, and managerial cognition—with firm-level dynamic capabilities (Abou-Foul et al., 2023; Al Halbusi et al., 2025; Javed et al., 2026; Wang & Zhang, 2026).

## 5. CONCLUSION

This SLR about AI capabilities in dynamic capabilities using the PRISMA protocol and the TCCM framework. Based on a final robust dataset of 35 core studies, the findings confirm that AI capability is increasingly conceptualized not merely as a standalone technological tool, but as a multidimensional organizational capability. Its true strategic value emerges only when firms embed AI into organizational routines to strengthen dynamic processes such as sensing, seizing, and reconfiguring, thereby fostering agility, resilience, and sustainability (Mikalef & Gupta, 2021; Teece, Pisano, & Shuen, 1997).

The TCCM synthesis reveals four key findings. First (Theory), the Dynamic Capabilities View remains the dominant theoretical lens for explaining AI-driven adaptation. Second (Context), empirical evidence is heavily concentrated in emerging economies, specifically within manufacturing SMEs and supply chain sectors. Third

(Characteristics), AI capability acts as a crucial catalyst that links digital transformation to innovation, supply chain resilience, circular economy practices, and sustainable performance outcomes. Fourth (Methodology), the field is overwhelmingly dominated by cross-sectional, quantitative structural equation modeling (SEM), highlighting a scarcity of qualitative, longitudinal, and process-based methodologies.

This review contributes to the strategic management literature by clarifying the theoretical positioning of AI capability. It demonstrates that AI functions as a powerful capability-enhancing mechanism that converts data, algorithmic power, human expertise, and operational routines into sustainable competitive advantages. This interpretation extends prior frameworks by explicitly showing how AI supports organizational adaptation in turbulent and resource-constrained environments (Ameen, Tarba, Cheah, Xia, & Sharma, 2024; Sjödin, Parida, & Kohtamäki, 2023).

Finally, this study identifies critical directions for future research. Scholars must clarify the precise ontological boundaries of AI capability—whether it operates as a foundational resource, an ordinary capability, or a higher-order dynamic capability in itself. Methodologically, the field urgently requires more longitudinal and mixed-method designs to capture how AI capabilities evolve over time. Ultimately, this review suggests that future inquiries should move beyond testing whether AI improves performance, to systematically examining how, when, and under what boundary conditions AI capability strengthens dynamic capabilities.

## 6. ACKNOWLEDGMENTS

No specific external funding was received for this research. The author(s) reported no potential conflicts of interest.

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