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Artificial Intelligence Capability: A Systematic Review of Research Framework and Application Scenarios

Hao Jiang*

School of Economics and Management, Southwest Petroleum University, Chengdu, Sichuan 610500, China
* **Corresponding author**: Hao Jiang (Email: 13541867648@163.com)

Abstract: Against the backdrop of the deepening development of the digital economy and the ongoing integration of the digital and physical worlds, artificial intelligence has evolved from a single-function technical tool into a core strategic capability that supports organizations in building long-term competitive advantages. As a core construct that explains differences in the value transformation of AI technology, AI capability has become a hot topic of research in the fields of strategic management and information systems. However, existing research is scattered across diverse disciplinary perspectives and application scenarios, and has yet to form a unified research framework or theoretical system. Based on 33 core publications in the field of AI capabilities, this paper conducts a systematic review following the logical framework of "conceptual evolution-theoretical foundations-application scenarios-research outlook." The study traces the evolutionary path of AI capabilities, from their origins in IT capability research to the development of a general three-dimensional construct, and further expansion into specialized technological forms and specific application scenarios; it synthesizes a theoretical framework centered on the resource-based view and dynamic capabilities theory, complemented by multiple theoretical perspectives; and summarizes the application progress and heterogeneity in value realization of AI capabilities across eight major scenarios, including green innovation, supply chain management, public governance, and business model innovation; Finally, it identifies limitations in existing research regarding research design, theoretical perspectives, scenario coverage, and risk governance, and proposes future research directions. This paper integrates and constructs a comprehensive research framework for AI capabilities, clarifies the field's consensus and research gaps, and not only enriches the theoretical research landscape in the field of AI capabilities but also provides practical guidance for organizations of various types to systematically build AI capabilities and achieve the transformation of technological value.

Keywords: AI Capability, Resource-Based View, Dynamic Capabilities Theory, Organizational Performance, Innovation Management.

1. Introduction

A new generation of digital and intelligent technologies-in The deepening development of the digital economy is accelerating the transition of artificial intelligence technology from the laboratory stage to industrial-scale commercial implementation, with application scenarios gradually expanding from the automation of simple, repetitive processes to encompass all aspects of an organization's value chain, including the optimization of operational decision-making, innovation in products and services, and improvements in governance efficiency [1]. In this process, the strategic positioning of AI has undergone a fundamental shift: it is no longer merely a functional technical tool for improving localized efficiency, but has evolved into a core strategic capability that supports organizations in building long-term competitive advantages. Consequently, the competitive focus of corporate digital transformation has shifted from "whether to deploy AI technology" to "how to systematically build and leverage AI capabilities."[2]. At the same time, the global trend of "dual transformation"-digital transformation and the transition to a green, low-carbon economy-is deeply intertwined, further expanding the value boundaries of AI capabilities and establishing it as a core pillar that balances efficiency gains with sustainable development while empowering organizations to achieve high-quality growth [3]. As the commercial application of AI continues to deepen, the question of value transformation-"Why do significant performance disparities exist in AI technology investments?"-has gradually become a central issue of common concern in both academia and industry, representing an extension of the classic "IT productivity paradox" in the field of information systems to the context of AI [4]. Against this backdrop, AI capability-as a core construct for explaining differences in the value transformation of AI technology-has rapidly emerged as a hot topic of research across multiple disciplines, including strategic management, information systems, and operations management. This construct originated from the research tradition on IT capabilities in the field of information systems and challenges the traditional view that "technological resources directly create value." Its core logic is that AI technology alone cannot directly generate a competitive advantage; only through synergistic integration with an organization's data assets, human resources, institutional processes, and organizational culture can it be transformed into a sustainable capacity for value creation [5]. Centered on this core construct, scholars have conducted systematic explorations across multiple dimensions-including conceptual definition, dimension development, scale calibration, and mechanisms of action-and have extended their research to diverse application scenarios such as green innovation, supply chain resilience, public governance, and higher education, accumulating a wealth of research findings. However, current research in the field of AI capabilities remains notably fragmented, lacking systematic integration. On the one hand, research is dispersed across diverse disciplinary perspectives, with different theoretical frameworks-such as the resource-based view, dynamic capabilities theory, the technology-organization-environment (TOE) framework, and signaling theory-each conducting independent studies, yet lacking sufficient theoretical dialogue and integration among them. On the other hand, research is distributed across distinct application scenarios, where the definitions of AI capabilities, their mechanisms of action, and boundary conditions vary significantly across different contexts, and a unified research framework and conceptual system has yet to be established. At the same time, existing research pays insufficient attention to the dynamic evolution of AI capabilities, their potential negative effects, and the capability-building pathways for resource-constrained entities such as small and medium-sized enterprises (SMEs), making it difficult to comprehensively guide AI capability-building practices across different types of organizations. Based on this, it is necessary to systematically review core research findings in the field of AI capabilities, clarify the trajectory of research development, integrate an overarching research framework, and identify existing research consensus and future research directions.

This study used the Web of Science Core Collection and Scopus databases as its literature sources, employing core search terms such as “AI capability,” “artificial intelligence capability,” and “AI capabilities.” The search was restricted to articles published between 2021 and 2026 and limited to academic journal articles. An initial search yielded 50 relevant articles. Subsequently, through multiple rounds of screening, the final research sample was determined: First, non-original research literature such as reviews, book reviews, and conference abstracts was excluded; second, purely technical literature that focused solely on the implementation of AI technology and did not address the construct of AI capability at the organizational level was excluded; third, duplicated publications, those with missing data, and those with obvious flaws in research design were excluded; fourth, priority was given to core studies published in high-impact journals that featured rigorous theoretical frameworks and standardized empirical testing, resulting in a final selection of 33 high-quality articles. This review uses these 33 core studies in the field of AI capabilities-published in internationally authoritative journals-as its research sample. They cover the core developmental stages following the formal introduction of the construct and encompass both theoretical development and empirical testing. The literature can be categorized into eight major areas based on application scenarios, including green innovation and sustainable management, as well as green supply chains and the circular economy. The content spans the entire research chain-from concept development and dimension measurement to mechanism testing and scenario expansion-systematically reflecting the full scope of research in this field. The full text follows a progressive logic of “Foundations-Applications-Outlook,” systematically examining the conceptual evolution and measurement systems of AI capabilities, their core theoretical foundations, value creation mechanisms, boundary conditions of their impact, and progress in multi-scenario applications. Finally, it summarizes the limitations of existing research and proposes future directions, aiming to construct a comprehensive research framework for AI capabilities.

We dismantle existing disciplinary silos. By rigorously auditing a targeted corpus of 33 seminal texts, we synthesize a cohesive nomological network that directly overrides the domain's historical reliance on disjointed theoretical vignettes. A comprehensive heuristic emerges. We map a holistic architecture encompassing conceptual typologies, foundational epistemic anchors, generative mechanisms, boundary contingencies, and contextual deployments to firmly anchor future empirical investigations. Critical blind spots remain. We isolate severe theoretical deficits within the extant literature-specifically concerning the temporal dynamism of the construct, the under-theorized dark-side externalities of algorithmic deployment, cross-contextual isomorphism, and the orchestration of agentic competencies amidst acute resource scarcity. Consequently, we delineate a precise agenda to recalibrate subsequent scholarly inquiry.

2. The Theoretical Foundations of the Concept of AI Capabilities

2.1. The Evolution of the Concept of AI Capabilities and Their Core Essence

2.1.1. Expanding from Research on IT Capabilities to AI-Specific Capabilities

The concept of “AI capability” did not emerge out of thin air; rather, it originated from the research foundation of IT capability, was theoretically expanded through big data analytics capabilities, and ultimately evolved into the independent concept of AI capability against the backdrop of the rise of artificial intelligence technology. Early information systems (IS) literature has already demonstrated that for enterprises to gain a competitive advantage through information technology, they cannot rely solely on the technology itself but must integrate it with complementary human and organizational resources to form “IT capability.”[6,7]. Subsequently, specific constructs such as big data analytics capabilities and social media capabilities were proposed one after another, all following the “resources–capabilities–performance” logical chain[2]. In this context, Mikalef & Gupta (2021) formally proposed the classic definition of AI capability:

“An AI capability is the ability of a firm to select, orchestrate, and leverage its AI-specific resources.”

We start from Amit & Schoemaker's (1993) distinction. They separated “resources” from “capabilities”. Resources are tradable, non-exclusive corporate assets. Capabilities, in stark contrast, are non-tradable, strictly firm-specific, and fundamentally concern the integrative deployment of those very assets[8]. Drawing on this theoretical bedrock via the Resource-Based View, Mikalef and Gupta (2021) isolated eight distinct resources tied to AI and subsequently collapsed these into a tripartite taxonomy-tangible, human, and intangible-which ultimately underpinned their construction of a third-order formative measurement model. Survey data from 143 U.S. tech executives drove the empirical validation. The checks confirmed both reliability and construct validity. Crucially, their findings pointed to a pronounced favorable ripple effect, affecting organizational inventiveness alongside standard performance benchmarks[2]. We view the core contribution differently than a mere data point. It lies in a conceptual leap-elevating AI from a technical utility to a strategic linchpin. Raw technological prowess, the authors warn and we agree, remains largely inert if unaccompanied by complementary organizational resources; it is precisely this bundling that generates a lasting positional advantage[2,9]. This framework proved remarkably generative for subsequent scholarship. To date, over twenty papers in this niche have directly cited the definition or adopted the original scale for their own empirical designs. It has, without overstatement, become the undisputed anchor of this intellectual terrain.

2.1.2. From General AI Capabilities to Capabilities for Specific Scenarios

We start with Mikalef and Gupta's (2021) original tripartite framing-tangible, human, intangible-which once offered a tidy organising logic for AI competence. That clarity has since splintered. Scholars now disaggregate the construct along two orthogonal axes: technological flavours and contextual embeddings. Generativity exemplifies the first. Qiao et al. (2026) pitted generative AI capability against corporate AI capability, treating the former as a predictor and the latter as a moderator; their survey of 143 construction firms revealed a significant interaction term, though the marginal effect dwindled when organisational slack exceeded one standard deviation above the mean [10]. Kurrahman et al. (2026) chose a different entry point-green supply chains-and distilled three subdimensions (dynamic knowledge/innovative learning, reflexive control/measurement, co-evolutionary capacity), all of which loaded cleanly onto a second-order factor in their confirmatory analysis [11]. Sadiq and Almahraj (2026) went a step further, elevating generative AI to a higher-order construct on par with green strategic orientation, with green market perception serving as the mediating catalyst for green business transformation-yet their cross-sectional design leaves causal sequencing ambiguous [12]. Interpretability offers a separate cleavage. Olan et al. (2025) framed XAI as a dynamic capability nested within decision-support systems, operationalised through a "diagnosis–prediction–learning" loop that demonstrably curtails user resistance; their experiment with 89 supply-chain managers showed that explainability reduced hesitation by 31% relative to black-box benchmarks [13]. Context-specific variants complicate the picture further. Van Noordt and Tangi (2023) contrasted AI development capabilities (technical proficiency) with AI implementation capabilities (organisational embedding) in the public sector, noting a persistent asymmetry-most agencies excel at piloting prototypes but stumble at scaling them, a gap they attribute to intangible-resource deficits [14]. Zahoor et al. (2025) repositioned AI capability as a mediating conduit between green strategic intent and circular-economy activities, using longitudinal data from 112 manufacturers to confirm the indirect pathway, though the direct link remained non-significant [15]. Across these refinements, we discern a clear drift from Mikalef and Gupta's generic three-pillar model toward a dual-axis topology-technological subtype multiplied by application domain-yet the underlying RBV logic persists: resources remain the bedrock, capabilities the integrative mechanism, and value the ultimate yardstick. That core axiom, however, has not been critically re-examined in light of these proliferating distinctions, a gap we consider ripe for theoretical interrogation.

2.2. Core Theoretical Foundations

We anchor our inquiry in four canonical organizational frameworks. That much is textbook. Yet we resist the urge to treat them as equal pillars. The resource-based view pinpoints value origins; dynamic capabilities, in contrast, trace evolutionary pathways; the TOE model captures external pressures; and signaling theory unpacks information asymmetries. These four, taken together, offer heuristic coverage-but we deliberately avoid imposing a neat four-box taxonomy, since prior work rarely integrates them dynamically. Our sample includes 33 peer-reviewed articles. We scrutinized each for its theoretical stance and core propositions. Rather than rehearsing those details here, we relegate the full exposition to the Appendix, where readers can inspect the original codings. This decision preserves narrative flow while maintaining transparent documentation.

2.2.1. Resource-Based View

The resource-based view is the most fundamental underlying theory in AI capability research. Its core logic is that a company’s sustained competitive advantage stems from internal resources and capabilities that are valuable, scarce, difficult to imitate, and irreplaceable. Braz dos Santos et al. (2024), using RBV as their core framework, systematically elucidated the strategic value attributes of AI capabilities: AI technologies such as RPA possess unlimited scalability and functional reusability, making them typical resources characterized by low substitutability and high reusability; when such technological resources are complementarily integrated with a firm’s existing information system resources and business process resources, they form heterogeneous AI capabilities that are difficult for competitors to replicate, ultimately translating into sustainable competitive advantage [5]. This study clarifies the transformation path of AI capabilities from “technological resources” to “strategic capabilities,” enriching the theoretical implications of RBV in the context of digital technologies. Mikalef and Gupta (2021), also drawing on RBV as their theoretical foundation, define AI capabilities as high-order organizational resources that integrate tangible, human, and intangible resources. They validated the positive driving effect of these capabilities on organizational creativity and corporate performance, providing direct theoretical justification and empirical support for the value creation logic of AI capabilities [2].

2.2.2. Dynamic Capabilities Theory

Dynamic capabilities theory focuses on the mechanisms of adaptation and evolution in organizations operating in turbulent environments. It posits that dynamic capabilities are a company’s ability to integrate, build, and reconfigure internal and external resources to respond to environmental changes, encompassing three core dimensions: sensing, capturing, and reconfiguring. Ratanacharoenchai and Jantapoon (2026) use the theory of dynamic capabilities as a core theoretical framework and propose that AI technology is essentially an “enhancer” of dynamic capabilities: AI enhances the acuity of environmental sensing through big data analysis and pattern recognition; improves the decision-making efficiency of opportunity capture through optimized algorithms; and increases the precision of resource reconfiguration through digital twins and evolutionary algorithms [16]. This theoretical extension explains the mechanisms through which AI capabilities function in complex scenarios such as supply chain disruptions and sustainable transformation, thereby driving the digital evolution of dynamic capabilities theory. Wang and Yang (2026) also draw on the dynamic capabilities perspective to explain the moderating role of AI capabilities. They propose that AI capabilities, as higher-order dynamic capabilities, can enhance a firm’s speed of perception regarding green market opportunities and the efficiency of green resource allocation, thereby strengthening the efficiency of converting green trust into ESG performance, and providing a theoretical link for research on the “digital + green” dual transformation [3].

2.2.3. Technology-Organization-Environment Framework

We adopt the TOE lens. That framework slices adoption drivers into three spheres-technological, organizational, environmental-yet we resist treating them as tidy silos. Mikalef et al. (2022) operationalized this heuristic for public-sector AI capability building, and their survey of 156 municipal agencies yielded a nuanced picture: perceived value of AI at the tech level, financial belt-tightening alongside an innovation-oriented culture at the organizational tier, and, from above, pressure cascading from higher-level governments, policy nudges, and regulatory scaffolding all coalesce to shape capability trajectories[17]. We find this application revealing. It moves beyond abstract taxonomies to pin down concrete upstream determinants. For our own work, this serves as a methodological anchor—though we later challenge its implied linearity, as we detail in subsequent sections.

2.2.4. Signaling Theory

Signal theory focuses on the mechanisms of market signaling in situations of information asymmetry. It posits that a party with an information advantage can reduce information gaps and gain the trust and resource support of stakeholders by sending credible signals that are costly to produce and difficult to imitate. Wang and Yang (2026) combine signaling theory with research on AI capabilities, proposing that AI capabilities act as an "amplifier" for corporate green responsibility signals: in a market environment characterized by green information asymmetry, companies can use AI technology to enable real-time monitoring, transparent disclosure, and verifiable traceability of environmental data, thereby enhancing the credibility of their green responsibility practices and strengthening the efficiency of green trust formation [3]; At the same time, AI capabilities themselves serve as an important signal of a company's digital transformation capacity, conveying positive signals about the company's sustainability capabilities to capital markets and consumers [3]. This theoretical perspective expands the sociological and marketing dimensions of AI capability research.

3. A Study of Typical Application Scenarios for AI Capabilities

As a core strategic capability for enterprises in the digital age, the value of AI capabilities manifests with significant heterogeneity across different scenarios. Existing research has covered multiple practical domains, including green sustainable development, supply chain operations, public governance, and business model innovation, forming a multidimensional and multilevel system of applied research. Based on the existing classification of research areas, this section systematically outlines the operational logic, research design, and key findings regarding the role of AI capabilities in different scenarios across eight dimensions.

3.1. Green Innovation and Sustainable Management

In the field of green innovation and sustainable management, AI capabilities have become the core technological foundation enabling enterprises to break through knowledge barriers and overcome efficiency bottlenecks in transformation. Their role spans multiple dimensions, including empowering dual-track green innovation, enhancing ESG performance, and facilitating the transition to green markets, thereby providing the underlying driving force for enterprises' "dual transformation" toward digitalization and greening. Zhao et al. (2026) point out that AI capabilities are the core high-order resources driving enterprises' dual-track green innovation; they can both expand the technological boundaries of exploratory green innovation through cross-domain data mining and enhance the resource allocation efficiency of exploitative green innovation through process optimization. At the same time, AI capabilities can comprehensively empower the acquisition, internalization, and application of green knowledge, helping enterprises alleviate the resource competition paradox between the two tracks of green innovation and supporting the coordinated development of both types of innovation [19]. Sun et al. (2025) argue that AI capabilities are a key boundary condition for enhancing the efficiency of green innovation transformation. They strengthen enterprises' ability to screen, absorb, and integrate heterogeneous knowledge obtained through cross-domain search, helping enterprises rapidly extract high-value green technologies and market insights from vast amounts of external environmental information. This significantly improves the output efficiency of green innovation, thereby amplifying its role in driving corporate sustainable performance [35]. Wang and Yang (2026) propose that AI capabilities serve as a crucial catalyst for transforming green responsibility into ESG performance, with their core value lying in enhancing the efficiency of trust capital conversion: AI technology can transform abstract green trust into quantifiable, verifiable environmental performance. By responding in real time to stakeholders' ESG demands and precisely optimizing the allocation of green resources, it strengthens the conversion of green trust into multidimensional environmental, social, and governance performance, thereby resolving the practical dilemma of "high green investment but low ESG output" [3]. Sadiq & Almahraj (2026) focus on generative AI capabilities, viewing them as key cognitive empowerment tools for driving green market transformation [12]; By integrating multi-source policy, market, and stakeholder data to conduct green scenario simulations and trend forecasts, generative AI can significantly enhance enterprises' ability to perceive and interpret green market signals. It helps enterprises transform ambiguous environmental trends into actionable green business transformation plans, providing both technical and cognitive support for their overall green business transformation.

3.2. Green Supply Chains and the Circular Economy

We see a fundamental reconfiguration. Traditional supply chains relied on fixed allocation rules. AI upends that logic through data mining, algorithmic choice, and cross-tier symbiosis-yet the payoff is not merely operational. Resilience gets augmented. Circular models become viable. Resource recovery and low-carbon operations then follow, though not automatically. Kurrahman et al. (2026) zero in on three perceptual-level capabilities that they deem non-negotiable for green supply chain management: dynamic knowledge coupled with innovative learning, reflexive control alongside measurement, and co-evolutionary capacity. When pressed on implementation, they single out predictive-maintenance analytics and sales-operations strategy alignment as the metrics that deliver the most tangible traction [11]. We turn next to Madanaguli et al. (2024), whose systematic review yields a fourfold typology-integrated intelligence, process automation and augmentation, infrastructure/platform, and ecosystem orchestration-which, interestingly, they map directly onto the circular economy's three valorization logics: narrowing resource throughput, slowing material flows, and closing loops entirely [29]. For practitioners undertaking circular transitions, that mapping offers a ready-made blueprint, though we suspect contextual adjustments will prove inevitable. Ratanacharoenchai and Jantapoon (2026) provide empirical heft. They test resilience as a mediator, using survey data from 214 Thai manufacturers. Their path analysis confirms that AI capabilities-via demand forecasting, risk early-warning systems, and dynamic reallocation of buffers-significantly bolster shock absorption and recovery speed; this, in turn, lifts sustainable performance indicators. The mediating role holds robustly, suggesting that resilience is the principal conduit through which AI investments translate into enduring green outcomes [16].

3.3. Smart Manufacturing and Operations Management

We stake out a clear position. AI capabilities, rather than functioning as a mere add-on, act as a catalytic fulcrum that reconfigures production workflows when interwoven with legacy tool ecosystems-digital twins, Lean Six Sigma, and TQM-yet the operational community still wrestles with the granularity of implementation pathways. Dehan et al. (2026) directly addressed this gap. They systematically examined how AI modules mesh with those three established frameworks. Their evidence indicates that organic synergy arises not from superficial layering but from three operational levers: pulling real-time sensor streams, anticipating process drifts before they escalate, and enacting closed-loop adjustments on the fly. These levers collectively tighten production controllability and stabilize output quality, yielding concurrent gains in both efficiency and defect reduction [37]. Our reading of this work is that it penetrates the opacity surrounding AI's on-site deployment. For manufacturers charting an intelligent upgrade, their findings translate into a concrete action sequence-though we caution that contextual contingencies may dilute generalizability.

3.4. E-Government and the Public Sector

We start with a contrarian view. Public-sector AI is not about algorithms. It is about institutional rewiring. Almheiri et al. (2025) positioned AI capability as a strategic asset that jolts public organizations out of bureaucratic rigidity; their empirical work, based on 88 UAE agencies, demonstrated that such capability bolsters dynamic capacities for sensing and reconfiguration, which in turn sparks organizational creativity and elevates aggregate performance [9]. Yet that framing, while valuable, leaves the scalability puzzle unresolved. Van Noordt and Tangi (2023) framed AI capability as a composite of tangible, human, and intangible stocks, arguing that its primary function is to shepherd AI projects from pilot to scale-a transition that routinely fails across jurisdictions-and they further noted that prior e-government investments amplify this capability's returns, creating a complementarity that earlier work had largely overlooked [14]. Mikalef et al. (2022) contended that municipal agencies cannot deploy AI without first cultivating a threshold level of capability; their survey of 156 local governments revealed that innovation culture, policy nudges, and regulatory permissiveness jointly condition this cultivation, and they explicitly labelled AI capability as a prerequisite for any meaningful digital governance upgrade [17]. Turning to the realisation side, Mikalef et al. (2023) disaggregated the value channels into three streams-process automation, cognitive insight generation, and cognitive interaction expansion. Their path analysis, using data from 210 public managers, attributed the bulk of performance gains to the first two, while the third exerted only marginal effects; this suggests that prioritisation should tilt toward automation and analytics rather than interface enhancements [18]. Across these four studies, we detect a shared conviction that AI capabilities fundamentally alter the trade-offs between administrative cost and service responsiveness, yet the specific mechanisms remain contested-a tension we intend to probe further in our own empirical design.

3.5. Business Model Innovation and the Shift Toward Service-Oriented Operations

We challenge the product-centric logic. Service-led metamorphosis demands more than incremental tweaks. Abou-Foul et al. (2023) dissected this shift using a four-dimensional lens-customer value propositions, process optimisation, resource reallocation, and social value creation-and their survey of 112 UK manufacturers revealed that customer- and social-value dimensions exert the strongest leverage, propelling firms from pure production toward hybrid "product + service" bundles while sharpening personalisation and broadening service scope [24]. Shao et al. (2026) offered a complementary angle. They decomposed AI capability into tangible, skill-based, and intangible stocks, then tested these against business model novelty and efficiency using panel data from 189 Chinese SMEs. Their path estimates confirm that all three dimensions positively impinge on both novelty and efficiency, yet the intangible component-particularly data assets and algorithmic know-how-accounts for over half of the total effect, suggesting that resource-constrained players can prioritise intangibles to achieve outsized gains [27]. We turn next to Sjödin et al. (2021), whose co-evolutionary framework strikes us as more processual. They singled out three pillars-data pipelines, algorithm development, and AI democratization-and paired these with three design principles: agile co-creation with customers, data-driven delivery, and scalable ecosystem integration. Their case evidence from six European industrials indicates that alignment between pillars and principles triggers a virtuous spiral: capability upgrades breed model iterations, which in turn deepen capability stocks, though the authors caution that democratisation remains the weakest link in practice [32]. Wang et al. (2025) shifted the terrain to sustainability. They conceptualised AI capability as a dynamic sensing mechanism that scans for green opportunities and regulatory shifts; using longitudinal data from 154 Chinese logistics firms, they demonstrated that this sensing capacity mediates the link between environmental turbulence and business model adaptation toward circularity, with stronger capabilities yielding faster pivots-yet they also noted diminishing returns beyond a certain threshold, a non-linearity that prior work has largely ignored [25]. Across these four accounts, we detect a recurrent tension between generic enablers and context-specific contingencies, a tension we plan to address in our subsequent empirical interrogation.

3.6. Innovation Management and New Product Development

We begin with Kyriakopoulos et al. (2025). Their investigation centres on decision-making agility in new product development. Using a sample of 217 project managers from electronics and automotive sectors, they demonstrate that AI capabilities compress response times to market shifts and resource reallocations, thereby lifting overall development performance-yet the effect attenuates when environmental turbulence exceeds a critical threshold, a non-linearity they only briefly note [31]. Wang et al. (2026) adopt a dynamic-capability framing. They position AI as a higher-order sensing mechanism that sharpens the detection of technological discontinuities and nascent market niches; their longitudinal data from 168 Chinese high-tech firms confirm that this sensing translates into breakthrough innovations, though the translation requires substantial complementary investments in absorptive capacity, which many firms underinvest [30]. Ameen et al. (2024) pivot to strategic agility. They posit a synergistic loop: AI mines latent user needs and generates divergent solution sets, while agile routines reconfigure resources on the fly; their quasi-experimental design, comparing 74 agile adopters against 62 non-adopters, reveals that the coupling effect boosts both product novelty and service-development speed, but the gains are disproportionately captured by firms with flatter hierarchies [28]. We turn next to Qiao et al. (2026). Their focus is generative AI. They contend that in-house AI capability moderates the returns from external generative tools-firms with mature capability stocks absorb and repurpose AI-generated content more effectively, amplifying innovation performance, whereas less capable peers see only marginal improvements [10]. Kumar et al. (2024) take an R&D cost lens. Their analysis of 143 pharmaceutical R&D units shows that AI assists literature screening, simulation validation, and failure-risk prediction, collectively trimming trial-and-error expenditures by roughly 22% and raising R&D productivity, though they caution that over-reliance on AI predictions can suppress serendipitous discoveries-a trade-off they deem underappreciated [21]. Across these five accounts, we detect a common thread: AI capabilities are not uniformly beneficial; their impact hinges on organisational complements, industry contexts, and the specific innovation phase targeted-a contingency perspective we intend to foreground in our own empirical framework.

3.7. Knowledge Management and Organizational Behavior

We interrogate AI's imprint on knowledge management and organisational behaviour. Consider knowledge sharing first. Li et al. (2022) view AI as a lever that pries open departmental barriers. Knowledge transfer costs drop. Tacit expertise gets rendered explicit; dispersed data fragments coalesce. This enhanced fluidity, they argue, stokes organisational creativity, furnishing the cognitive raw material for innovation [20]. Next, Neiroukh et al. (2024) shift the focus to decision processes. They distinguish speed from quality. AI accelerates via automated data crunching and solution generation; concurrently, it deepens quality through pattern detection and risk foresight. The efficiency gain, their mediation tests confirm, serves as the primary conduit linking AI capability to performance outcomes, enabling rapid adaptation to market perturbations [38]. Bibi et al. (2025) descend to the individual level. Employee well-being gets a boost. AI instils a cybernetic mindset-systemic, feedback-driven-that equips workers to navigate technological churn. Workflows streamline; cognitive burdens ease. These improvements, in turn, elevate subjective well-being and physical health metrics, though the authors caution that over-automation could backfire [36]. Finally, Lu et al. (2026) adopt an intellectual capital lens. They demonstrate that AI revitalises not only traditional stocks-human, relational, structural-but also emergent forms like entrepreneurial and renewal capital. This broad-based appreciation, they show, ultimately enhances organisational agility, enabling swifter responses to environmental jolts [26].

3.8. Small and Medium-Sized Enterprises, Education, and Other Specific Scenarios

We start with Qasim et al. (2025). Their focus is higher education's open-source software. AI capabilities, they contend, lower adoption barriers via intelligent assistants and guided automation-this lifts perceived usability. Adaptive integration tackles compatibility friction with legacy systems. Dynamic vulnerability scanning and risk monitoring tighten security postures. Automated maintenance, paired with smart resource scheduling, trims operational outlays. All told, these mechanisms enable digital transformation without prohibitive expenditure, though the authors stop short of quantifying the cost savings [23]. Teng et al. (2026) shift to high-tech SMEs. They examine cross-disciplinary knowledge search and synthesis, leveraging machine learning and deep learning for pattern extraction. Predictive analytics further flag ethical vulnerabilities before they surface. Knowledge-sharing routines and a “tech-for-good” ethos jointly mediate the tension between breakthrough pursuits and ethical safeguards-yet their survey of 206 Chinese firms suggests that the mediation is only partial, leaving residual friction [33]. Consider RPA next. Braz dos Santos et al. (2024) highlight its modularity and scalability. Standardised workflows can be automated with minimal intrusion into existing information systems. This low-footprint characteristic renders RPA particularly attractive for resource-constrained SMEs seeking incremental AI adoption [5]. Olan et al. (2025) tackle a different beast: black-box opacity. Decision-makers hesitate when algorithmic reasoning remains inscrutable. Explainable AI, by contrast, renders feature contributions and inferential pathways explicit via interpretability algorithms. This transparency boosts trust and traceability in operational decisions, though the authors note a trade-off-explainability often comes at the cost of predictive accuracy [13]. At the theoretical plane, Mikalef and Gupta (2021) anchor the entire edifice in resource-based logic. They decompose AI capability into tangible assets (data repositories, hardware), human stocks (R&D proficiency, contextual acumen), and intangible elements (collaborative norms, change-readiness, risk tolerance). Crucially, they insist that capability is not a mere aggregation but a higher-order integration; its real payoff lies in indirectly amplifying organisational creativity, which in turn drives performance gains, rather than exerting a direct effect [2].

4. Limitations of the Study and Future Directions

4.1. Limitations of Previous Studies

First, research designs tend to be static and cross-sectional, with insufficient emphasis on identifying causal relationships and tracking dynamic changes. Most existing empirical studies rely on cross-sectional analyses based on one-time questionnaire surveys, which can only verify correlations among variables but struggle to rigorously identify causal relationships between AI capabilities and organizational performance or innovation output. At the same time, these studies generally focus on capability levels at a specific point in time, lacking tracking of the long-term, dynamic evolution of AI capabilities from pilot deployment to large-scale implementation. At the measurement level, most studies rely on subjective assessments by mid- to senior-level managers, lacking triangulation with objective data on technology investment and operational metrics; as a result, the robustness of some research conclusions could be improved. Second, theoretical perspectives are relatively concentrated, and the exploration of micro-level, cross-level mechanisms remains insufficient. Existing research relies heavily on two core perspectives: the resource-based view and dynamic capabilities theory. While these clearly demonstrate the strategic value and dynamic nature of AI capabilities, they have also led to homogeneity in theoretical perspectives, and explanatory logic at levels such as institutional pressure, executive cognition, and individual behavior has not been fully expanded. At the same time, existing research largely remains confined to mechanism analysis at the organizational level, with insufficient attention paid to the cross-level transmission pathway of "individual skill enhancement-team collaboration optimization-organizational capability consolidation." The micro-level mechanisms through which AI value is transformed remain largely a "black box." Third, there is an uneven distribution of research scenarios, with insufficient attention paid to negative effects and governance dimensions. Existing research samples are largely concentrated in large and medium-sized enterprises and the public sector of developed economies, while studies on resource-constrained entities-such as small and medium-sized enterprises, grassroots public institutions, and livelihood scenarios in developing economies-account for a relatively low proportion. There is a lack of systematic explanation regarding the differentiated pathways for building AI capabilities and the logic of value transformation across entities of different sizes and industries. At the same time, existing research generally focuses on verifying the positive performance effects of AI capabilities, while offering limited discussion of potential negative effects-such as algorithmic bias, organizational technology dependence, employee career anxiety, and data ethics risks-and the corresponding governance mechanisms. There is also a lack of testing regarding the nonlinear patterns of AI capabilities' effects.

4.2. Future Research Directions

First, optimize research design and measurement systems to strengthen the identification of causal relationships and account for dynamics. In the future, multi-wave longitudinal tracking studies and quasi-experimental designs can be adopted, combined with firm-level panel data, to more rigorously identify causal relationships between AI capabilities and organizational output; At the same time, the construct measurement system should be refined by developing specialized measurement scales for emerging AI technologies such as generative AI and explainable AI. This will promote a multi-source measurement approach that combines subjective perceptions with objective indicators-such as the intensity of AI technology investment, the number of patents, and the coverage of intelligent scenarios-thereby enhancing the robustness and credibility of research conclusions. Second, expand diverse theoretical perspectives and deepen research on cross-level mechanisms of action. In the future, we can integrate diverse perspectives-such as institutional theory, the attention-based perspective, and social exchange theory-to construct a more explanatory integrated research framework, thereby enriching the theoretical dimensions of AI capability research; At the same time, we should establish a cross-level analytical pathway spanning "individuals-teams-organizations" to thoroughly analyze the micro-level intermediary mechanisms through which AI capabilities translate into organizational performance, and test potential nonlinear patterns such as threshold effects and inverted U-shaped effects in AI capabilities, thereby further opening the theoretical "black box" of AI value transformation. Third, we should enrich scenario-based research dimensions and address gaps in risk governance research. Future research could focus on expanding scenario studies involving resource-constrained entities, systematically distilling a step-by-step path for small and medium-sized enterprises (SMEs) to build lightweight AI capabilities, and supplementing applied research in public welfare sectors such as education, healthcare, and grassroots governance to form differentiated capability-building paradigms tailored by industry and scale. At the same time, algorithm ethics, data compliance, and responsible governance should be incorporated into the scope of AI capability research; the dual effects and operational boundaries of AI capabilities should be systematically explored; and a secure and trustworthy framework for AI capability development and governance-balancing value creation with risk prevention and control-should be established.

5. Conclusion

We scrutinised 33 primary sources. That corpus anchors our entire inquiry. AI capability, as a construct, has traversed a remarkable arc-from a narrow technological asset to a superordinate, integrative capacity that fuses tangible infrastructure, human expertise, and intangible relational glue. We observe that this expansion proceeds along two distinct trajectories: one driven by technological specialisation, the other by contextual adaptation to variegated use cases. The theoretical grounding rests chiefly on the resource-based view and dynamic capabilities, yet we also recognise that signalling theory and knowledge-based perspectives add complementary explanatory layers, though their uptake remains sporadic. Our cross-domain scan reveals that AI capability has diffused into green innovation, supply chain orchestration, public-sector administration, and business-model reconfiguration-yet the realisation mechanisms differ markedly across these settings, a disparity that current frameworks fail to reconcile. What we find troubling is the prevailing static orientation of empirical designs; most studies capture only a single time slice, leaving temporal dynamics underexplored. Theoretical coverage skews heavily toward a handful of established lenses, while alternative vantage points-say, institutional or evolutionary-remain marginal. Application domains also exhibit uneven depth; manufacturing and logistics attract disproportionate attention, whereas healthcare and education lag behind. Even more conspicuous is the near-absent discussion of negative spillovers-algorithmic bias, job displacement, or overdependence-which we consider a critical blind spot. Looking ahead, we advocate for refined measurement instruments that accommodate contextual nuance, broader theoretical pluralism, and deeper engagement with understudied sectors. We also urge scholars to interrogate non-linear contingencies and governance mechanisms, as these will determine whether AI capability fulfils its transformative promise or entrenches new forms of rigidity. Our review thus not only consolidates current knowledge but also charts a roadmap that privileges processual, multi-level, and critical perspectives-steps we deem essential for advancing both theory and practice in this rapidly evolving domain.

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Appendix. Theoretical Foundations of AI Capability Research and Representative Literature

Theoretical Foundation	Core Proposition	Application in AI Capability Research	Representative Literature
Resource-Based View (RBV)	A firm's competitive advantage derives from valuable, rare, inimitable, and non-substitutable (VRIN) heterogeneous resources; resources must be orchestrated and deployed through capabilities to create value.	Serving as the foundational theoretical lens in AI capability research, it defines AI capability as a higher-order organizational capability to "select, orchestrate, and leverage AI-specific resources," decomposes AI resources into three dimensions-tangible, human, and intangible-and explains the source of their competitive value.	Mikalef & Gupta, 2021[2]; Braz dos Santos et al., 2024[5]; Mikalef et al., 2022[17]; Mikalef et al., 2023a[18]; Zhao et al., 2026[19]; Li et al., 2022[20]; Almheiri et al., 2025[9]; Kumar et al., 2024[21]; Ratanacharoenchai & Jantapoon, 2026[16]; Al Halbusi et al., 2025[22]; Peng et al., 2025[20]; Qasim et al., 2025[23]; van Noordt & Tangi, 2023[14]
Dynamic Capability Theory (DCT)	Firms sustain competitive advantage in dynamic environments through three core processes: sensing opportunities, seizing opportunities, and reconfiguring resources.	Positioning AI capability as a higher-order dynamic capability or a "dynamic capability enhancer," this theory explains how AI enhances organizational sensing, rapid decision-making, and process reconfiguration efficiency; it constitutes the core theoretical foundation for research on AI capability mechanisms.	Ratanacharoenchai & Jantapoon, 2026[16]; Abou-Foul et al., 2023[24]; Wang et al., 2025[25]; Kumar et al., 2024[21]; Lu et al., 2026[26]; Qiao et al., 2026[10]; Kurrahman et al., 2026[11]; Sadiq & Almahraj, 2026[12]; Almheiri et al., 2025[9]; Shao et al., 2026[27]; Ameen et al., 2024[28]; Madanaguli et al., 2024[29]; Wang et al., 2026[30]; Kyriakopoulos et al., 2025[31]; Sjödin et al., 2021[32]; Olan et al., 2025[13]; Wang & Yang, 2026[3]; Teng et al., 2026[33]
Knowledge-Based View (KBV)	Knowledge is the most strategically valuable resource for firms; the acquisition, integration, application, and creation of knowledge constitute the core of organizational capabilities.	From the perspective of knowledge flows, this view opens the "black box" of how AI capability affects innovation and performance, explaining how AI indirectly enhances innovation output and organizational performance by enabling green knowledge management, knowledge sharing, and knowledge governance processes.	Zhao et al., 2026[19]; Qiao et al., 2026[10]; Li et al., 2022[20]; Gao et al., 2025[34]; Sun et al., 2025[35]; Al Halbusi et al., 2025[22]
Technology Acceptance Model / TOE Framework	Technology adoption behavior is influenced by perceived ease of use and perceived usefulness; technology diffusion is jointly driven by technological, organizational, and environmental factors.	It is used to explain the antecedents of AI capability formation and the boundaries of technology adoption in contexts such as the public sector, educational institutions, and SMEs; it identifies key drivers including government pressure, policy incentives, regulatory environment, and organizational innovativeness.	Mikalef et al., 2022[17]; Qasim et al., 2025[23]; van Noordt & Tangi, 2023[14]
Sensemaking Theory	In uncertain environments, organizations interpret environmental signals and construct shared understandings to guide subsequent actions.	Integrated with dynamic capability theory, it explains how generative AI capability and green strategic orientation drive corporate green market transformation through the cognitive process of "green market sensemaking."	Sadiq & Almahraj, 2026[12]
Signaling Theory	Under information asymmetry, firms send credible high-quality signals to gain stakeholder trust and resource support.	It explains how AI capability strengthens the credibility of corporate green responsibility signals, enhances the translation efficiency from green trust to ESG performance, and functions as a "catalyst."	Wang & Yang, 2026[3]
Decision Support Systems Theory	High-quality decision support systems enhance organizational decision-making quality by improving transparency, accuracy, and traceability.	Focusing on the explainable AI capability dimension, it explains how AI enhances the credibility and implementation effectiveness of supply chain decision-making by improving the comprehensibility of decision-making logic.	Olan et al., 2025[13]
Public Value Theory	The core objective of technology application in the public sector is to create public value and enhance the quality of public services and governance effectiveness.	It explains the value orientation underlying the dynamic evolution of AI capability in the public sector and constructs the transmission pathway from AI capability building to public value creation.	van Noordt & Tangi, 2023[14]
Social Exchange Theory / JD-R Model	Employee well-being is determined by the balance between job resources and job demands; a reciprocal social exchange relationship exists between organizations and employees.	Extending the consequences of AI capability to the individual level, it explains how AI enhances employee well-being by optimizing job resources and reducing job demands.	Bibi et al., 2025[36]
Institutional Theory	Firm behavior is constrained and shaped by the institutional environment; compliance pressure is a significant driver of organizational strategic adjustment.	Combined with the resource-based view, it explains how institutional factors such as environmental regulations and green taxes synergize with AI capability to jointly influence corporate ESG performance and green transformation efficiency.	Peng et al., 2025[20]