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Strategic Technology Adoption and Competitive Advantage: A Dynamic Capabilities Framework for Enterprise AI and Digital Innovation

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Abstract: **Digital transformation and artificial intelligence adoption present both opportunities and challenges for enterprises seeking sustainable competitive advantage. Yet technology adoption alone does not guarantee superior performance. Through a structured review of several studies identified via systematic search of the Web of Science and Scopus databases (2015–2024), this paper synthesizes research on strategic technology adoption through the lens of dynamic capabilities theory. We propose an integrated Strategic Technology Adoption Model (STAM) comprising five iterative stages: environmental scanning, strategic alignment assessment, capability development, technology integration, and continuous reconfiguration. The review identifies absorptive capacity, strategic alignment, and platform orchestration capabilities as critical mediators between technology adoption and competitive outcomes, while environmental dynamism, organizational agility, and governance structures moderate these effects. Drawing on micro-foundational analysis at individual, process, and structural levels, the paper derives twelve testable propositions specifying conditions under which enterprise AI enhances sensing, seizing, and reconfiguring capabilities. The STAM model advances existing frameworks, including those of Vial (2019) and Warner and Wäger (2019) by integrating AI-human substitution-complementarity dynamics and ecosystem-level orchestration mechanisms absent from prior models. Practical implications address capability-building priorities for enterprises navigating digital disruption.**

Keywords: **dynamic capabilities, strategic technology adoption, competitive advantage, enterprise AI, digital transformation.**

1. INTRODUCTION

Global enterprise spending on digital technologies and artificial intelligence now exceeds trillions of dollars annually, yet the majority of digital transformation initiatives fail to deliver their expected returns. This striking gap between investment and outcome points to a deeper puzzle: the problem lies not in the technologies themselves but in how organizations build the capabilities to exploit them. The strategic imperative to adopt digital technologies and enterprise AI has never been greater, but the path from adoption to advantage remains poorly understood. However, technology adoption alone does not guarantee superior performance; rather, competitive outcomes depend on organizational capabilities that enable firms to sense environmental changes, seize technological opportunities, and reconfigure resources in response to evolving market conditions (Teece, 2007).

This fundamental insight from dynamic capabilities theory provides a powerful lens for understanding why some organizations successfully leverage digital technologies while others struggle despite substantial investments. The intersection of strategic technology adoption and dynamic capabilities theory represents a critical area of inquiry for both scholars and practitioners. Recent research has begun to illuminate specific mechanisms through which digital technologies enhance sensing, seizing, and reconfiguring capabilities (Hercheui & Ranjith, 2020; Sullivan & Wamba, 2024), yet a

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comprehensive framework integrating these insights remains elusive. The challenge is particularly acute in the context of enterprise AI, where the transformative potential of machine learning, natural language processing, and predictive analytics intersects with complex organizational, ethical, and governance considerations (Abuzaid, 2024; Siaw & Ali, 2024).

This paper addresses three interrelated research questions: First, how do dynamic capabilities theory and strategic technology adoption frameworks converge to explain technology-driven competitive advantage? Second, what organizational capabilities and contextual factors mediate and moderate the relationship between technology adoption and performance outcomes? Third, what integrated model can guide enterprises in strategically adopting AI and digital technologies to build sustainable competitive advantage? By synthesizing contemporary scholarship across these domains, this review develops a Strategic Technology Adoption Model (STAM) that bridges theoretical foundations with practical implementation pathways. The contribution of this work is threefold. Theoretically, the paper integrates dynamic capabilities theory with technology adoption research, identifying specific microfoundations and capability-building mechanisms that link technology investments to competitive outcomes.

Analytically, the structured synthesis identifies convergent patterns across multiple studies regarding mediating roles of absorptive capacity, strategic alignment, and organizational agility in technology-driven performance gains. Practically, the STAM model provides a structured framework for enterprises to assess readiness, develop capabilities, and implement digital technologies in ways that enhance rather than merely automate existing processes. The remainder of this paper proceeds as follows. Section 2 describes the methodology employed for the structured literature review. Section 3 reviews literature on dynamic capabilities frameworks, strategic technology adoption models, competitive advantage mechanisms, and platform strategies. Section 4 presents the theoretical framework, detailing the five-stage STAM model and the Dynamic Capabilities Framework for digital innovation, along with formal propositions. Section 5 synthesizes findings across themes, examining mediating mechanisms, moderating factors, and emerging considerations in AI-human complementarity. Section 6 discusses theoretical contributions and practical implications, while Section 7 concludes with future research directions.

2. METHODOLOGY

This study employs a structured literature review methodology following established protocols for systematic evidence synthesis (Tranfield et al., 2003; Snyder, 2019). The review was conducted in three phases: identification, screening, and analysis.

2.1 Search Strategy and Databases: The primary search was conducted across the Web of Science Core Collection, Scopus, and ABI/INFORM Complete databases. The search covered publications from January 2015 to December 2024 to capture the most relevant contemporary scholarship on digital transformation and AI-enabled dynamic capabilities. Search strings combined terms from three clusters: (a) "dynamic capabilities" OR "sensing seizing reconfiguring" OR "organizational capabilities"; (b) "technology adoption" OR "digital transformation" OR "artificial intelligence" OR "enterprise AI"; and (c) "competitive advantage" OR "firm performance" OR "innovation outcomes". Searches used Boolean AND operators across clusters.

2.2 Inclusion and Exclusion Criteria: Studies were included if they: (a) were published in peer-reviewed journals, (b) addressed the intersection of dynamic capabilities and technology adoption or digital transformation, (c) were written in English, and (d) provided theoretical or empirical contributions relevant to competitive advantage mechanisms. Conference papers, book chapters, editorial commentaries, and teaching case studies were excluded from the primary analysis but could be referenced for illustrative purposes only. Studies focused exclusively on individual-level technology acceptance without organizational capability dimensions were excluded.

2.3 Screening and Selection Process: The initial search yielded 100 records. After removing duplicates, 40 unique records remained. Title and abstract screening reduced the pool to 35 articles. Full-text review against the inclusion criteria resulted in a final sample of 30 studies. A PRISMA flow diagram (Figure 3) documents the screening process.

2.4 Analysis Approach: Selected studies were coded along five dimensions: (a) theoretical framework employed, (b) technology type examined, (c) dynamic capability dimension addressed (sensing, seizing, reconfiguring), (d) research methodology, and (e) key findings regarding mediating and moderating mechanisms. Thematic synthesis following Braun and Clarke (2006) was used to identify convergent patterns across studies and to derive the integrative STAM framework presented in Section 4.

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3. LITERATURE REVIEW

3.1 Dynamic Capabilities Theory and Digital Transformation

Dynamic capabilities theory, originally articulated by Teece, Pisano, and Shuen (1997), posits that competitive advantage in rapidly changing environments stems from organizational capabilities to sense opportunities and threats, seize opportunities through resource mobilization, and reconfigure assets to maintain alignment with the evolving environment. This tripartite framework, sensing, seizing, and reconfiguring, has proven particularly relevant for understanding technology-driven strategic change in the digital era.

Importantly, the nature and characteristics of dynamic capabilities remain debated. Eisenhardt and Martin (2000) challenged the assumption that dynamic capabilities are inherently unique, arguing instead that they consist of identifiable "best practices" whose value depends on the market dynamism in which they are deployed. Helfat et al. (2007) further refined the concept by distinguishing dynamic capabilities from their outcomes, emphasizing that having a dynamic capability does not guarantee organizational fitness. These foundational distinctions matter for the present review because they caution against treating any technology-enabled organizational routine as a dynamic capability without assessing its actual contribution to evolutionary fitness. More recently, Vial (2019) provided one of the most comprehensive reviews of digital transformation research, identifying disruptions triggered by digital technologies and the strategic responses organizations adopt, including changes to value creation paths, structural adjustments, and organizational barriers. Warner and Wäger (2019) built specifically on Teece's framework to propose a process model for building dynamic capabilities for digital transformation, identifying digital sensing, digital seizing, and digital transforming as distinct capability clusters with their own micro-foundations. These contributions establish the theoretical baseline against which the present paper's STAM model must be benchmarked.

Recent scholarship has extended dynamic capabilities theory to address digital transformation contexts, with particular attention to micro-foundational elements that enable capability development. Witschel et al. (2023) examined digital business model innovation through a micro-foundations lens, identifying challenges and responses at individual, process, and structural levels that shape sensing, seizing, and transforming capabilities. Their research emphasizes that capability formation is not merely an organizational-level phenomenon but depends critically on individual skills, decision routines, and governance structures. This micro-foundational perspective reveals why technology investments alone prove insufficient; successful digital transformation requires coordinated interventions across multiple organizational levels to build the routines and structures that constitute dynamic capabilities. The application of dynamic capabilities theory to artificial intelligence adoption has yielded important insights into how AI technologies enhance each capability dimension. Hercheui and Ranjith (2020) provided exploratory qualitative evidence that AI contributes to all three dynamic capabilities: improving environmental scanning and pattern recognition for sensing, enhancing decision support and opportunity evaluation for seizing, and enabling asset and process reconfiguration through automation and optimization for transforming. Their findings suggest that AI functions not as a standalone technology but as an enabler of dynamic capabilities when properly integrated with organizational processes and decision-making structures.

Platform-based digital ecosystems present distinctive contexts for dynamic capabilities development. Wang et al. (2022) analyzed how digital platform leaders organize innovation processes that map to and foster environmental scanning, innovation capability, and integrative capability at ecosystem scale. Their study of Taobao revealed six platform-specific innovation processes that platform leaders can manage to build sensing, seizing, and reconfiguring capabilities across entire ecosystems, not merely within individual firms. This ecosystem-level perspective extends dynamic capabilities theory beyond firm boundaries, recognizing that competitive advantage increasingly depends on orchestrating capabilities across networks of complementors, suppliers, and customers. The relationship between dynamic capabilities and strategic alignment has emerged as a critical theme in digital transformation research. Jacobs and Pretorius (2022) proposed a systems model linking technology-enabled value creation to strategic alignment, arguing that dynamic capabilities operate as enablers of the strategic alignment necessary for technology-driven value creation in Fourth Industrial Revolution contexts.

Their framework positions strategic alignment not as a static state but as a dynamic capability itself, the ability to continuously realign technology investments with evolving strategic priorities and market conditions. Theoretical extensions addressing AI-specific considerations have begun to appear in recent literature. Siaw and Ali (2024) extended dynamic capabilities theory by theorizing substitution and complementarity relationships between human intelligence and

AI across sensing, seizing, and reconfiguring processes. Their work highlights that organizations face strategic choices regarding whether AI substitutes for or complements human capabilities in each dimension, with significant implications for capability development, workforce strategy, and governance. The substitution-complementarity framework adds nuance to understanding how AI reshapes rather than simply enhances dynamic capabilities.

Sector-specific applications of dynamic capabilities theory have illuminated distinctive mechanisms for capability development across industries. Noronha et al. (2022) developed an IoT-focused model demonstrating how Internet of Things technologies build dynamic capabilities by reducing transaction costs, increasing predictability, and enhancing agility in cleantech contexts. Their research illustrates that different digital technologies may enhance dynamic capabilities through distinct mechanisms, suggesting that capability-building strategies should be tailored to specific technology characteristics and industry contexts.

3.2 Strategic Technology Adoption Frameworks

Strategic technology adoption research has evolved from diffusion-focused models to frameworks emphasizing strategic fit, network effects, and capability alignment. Contemporary adoption frameworks recognize that technology decisions are not merely technical choices but strategic commitments that shape competitive positioning and organizational capabilities. Koch and Windsperger (2017) advanced a network-centric view for digital competitive environments, recommending that firms actively shape digital environments and co-create value with network actors rather than relying solely on industry structure or resource-based templates. Their framework represents a departure from traditional adoption models that treat technology as an exogenous factor to be adopted or rejected. Instead, the network-centric perspective positions firms as active participants in shaping technological trajectories and ecosystem dynamics, with adoption decisions embedded in broader strategies for ecosystem orchestration and value co-creation. Empirical research has identified specific pathways through which technology adoption creates competitive advantage. Chen and Tsou (2007) developed an IT adoption model for financial firms, providing evidence that IT adoption enhances service innovation practices, which in turn drive competitive advantage.

Their study of Taiwanese financial institutions revealed that the adoption-to-advantage pathway is mediated by innovation capabilities, suggesting that technology investments must be coupled with capability development to yield performance gains. This finding reinforces the dynamic capabilities perspective that technology serves as an enabler rather than a direct source of advantage. The emergence of artificial intelligence has prompted development of AI-specific adoption frameworks addressing unique technical, organizational, and ethical considerations. Abuzaid (2024) outlined a comprehensive strategic AI integration methodology encompassing culture, ethics, infrastructure, and regulatory dimensions as critical decision factors when integrating AI into corporate decision-making. This multidimensional framework reflects the complexity of AI adoption, which extends beyond technical implementation to encompass workforce readiness, ethical governance, data infrastructure, and regulatory compliance. The breadth of considerations in AI adoption frameworks underscores that successful implementation requires coordinated attention to technical, organizational, and institutional factors.

Several foundational adoption frameworks provide essential theoretical scaffolding that this review must acknowledge. Rogers' (2003) Diffusion of Innovations theory identifies relative advantage, compatibility, complexity, trialability, and observability as determinants of adoption rates, offering a lens for understanding why some AI technologies diffuse more rapidly than others. The Technology-Organization-Environment (TOE) framework (Tornatzky & Fleischer, 1990) broadens the analysis beyond individual adopter characteristics to consider organizational readiness and environmental pressures, making it particularly relevant for enterprise-level AI adoption decisions. At the individual level, the Unified Theory of Acceptance and Use of Technology (UTAUT) developed by Venkatesh et al. (2003) integrates multiple adoption models and identifies performance expectancy, effort expectancy, social influence, and facilitating conditions as key predictors. While UTAUT operates at a different level of analysis than the present review, its insights into user-level adoption barriers remain relevant for understanding the microfoundational challenges of digital transformation (Witschel et al., 2023). Bharadwaj et al. (2013) made a seminal contribution by reconceptualizing IT strategy as fused with business strategy in the digital age, arguing that digital business strategy encompasses the scope, scale, speed, and sources of value creation enabled by digital resources. This fusion perspective underpins the strategic alignment construct central to the STAM model developed in this paper.

The integration of dynamic capabilities theory with technology adoption frameworks has yielded decision models that emphasize strategic alignment. Jacobs and Pretorius (2022) developed a dynamic capabilities-informed decision framework emphasizing strategic alignment between technology investments and organizational value-creation hierarchies to improve

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adoption effectiveness. Their framework provides diagnostic steps for assessing whether proposed technology investments align with strategic priorities and whether the organization possesses or can develop the capabilities necessary to extract value from the technology. This alignment-focused approach addresses a common failure mode in technology adoption: investments in powerful technologies that remain underutilized because they lack strategic fit or supporting capabilities. Context-specific adoption responses have emerged as an important theme in recent research.

Witschel et al. (2023) identified individual, process, and structural responses as components of successful digital business model innovation, implying that adoption decisions should be informed by diagnostic assessment of micro-foundational readiness. Their research suggests that effective adoption frameworks must incorporate mechanisms for identifying capability gaps at multiple organizational levels and prescribing targeted interventions to address those gaps before or during technology implementation.

3.3 Enterprise AI and Competitive Advantage Mechanisms

Understanding how enterprise AI and digital technologies create competitive advantage requires examining specific mechanisms through which these technologies influence organizational capabilities and performance outcomes. Recent empirical research has begun to identify these mechanisms with increasing precision, revealing that technology effects are mediated by organizational capabilities and moderated by contextual factors. Three AI-powered capabilities which include: automation, analytics, and relational, emerge as consistent predictors of an organization’s Adaptive Response to Market Changes, or ARMC (Sullivan & Wamba, 2024). ARMC, in turn, drives firm performance and both process and product innovation, though these effects are amplified under conditions of environmental hostility and dynamism. The implication is important: AI technologies do not confer competitive advantage directly. Instead, they build adaptive capabilities that matter most precisely when markets are turbulent and unpredictable. A large-scale synthesis of 150 case studies reinforces this view across diverse industries, AI investments yield performance gains only when process-oriented dynamic capabilities is strengthened This includes process innovation, resource reconfiguration and, strategic flexibility that sit between raw computing power and actual firm outcomes (Wamba-Taguimdje et al., 2020). Technology, in other words, is an enabler of capabilities, not a direct performance driver.

The picture is similar in small and medium enterprises, though the mediating mechanisms carry their own texture. In SMEs, AI assimilation strengthens two capabilities that jointly drive performance: absorptive capacity and customer agility. Critically, organizational agility moderates both pathways: an AI system is only as valuable as the organization’s speed in acting on what it reveals (Abdul Wahab & Radmehr, 2024). Absorptive capacity is the ability to recognize, assimilate, and apply external knowledge matters because AI generates insights that require human interpretation. Customer agility matters because analytics-driven personalization only creates value when the organization can act on it quickly. Financial performance outcomes of AI adoption have begun to receive empirical attention. Li et al. (2024) provided evidence that AI adoption affects corporate financial asset allocation decisions and improves financial outcomes in firms adopting AI technologies. Their research suggests that AI enhances financial performance through improved capital allocation, risk management, and investment decision-making, representing a specific mechanism through which AI creates shareholder value beyond operational efficiency gains.

Application domain research has identified concrete pathways through which enterprise AI produces operational efficiencies and strategic advantages. Gupta et al. (2024) reviewed enterprise AI applications across supply chains, predictive maintenance, customer service, and decision support, documenting how AI produces value when aligned with regulation and risk controls. Their analysis revealed that AI's competitive impact varies by application domain: supply chain AI primarily enhances efficiency and responsiveness, predictive maintenance AI reduces costs and improves asset utilization, customer service AI improves satisfaction and retention, and decision support AI enhances strategic decision quality. This domain-specific perspective suggests that AI adoption strategies should be tailored to the specific competitive mechanisms most relevant to each application area.

The substitution-complementarity framework introduced by Siaw and Ali (2024) adds theoretical nuance to understanding AI's competitive mechanisms. Their analysis suggests that the choice between AI-human substitution and complementarity determines whether AI primarily supports external sensing or internal analytics, affecting how AI contributes to capability formation and competitive advantage. Substitution strategies may yield cost advantages through automation, while complementarity strategies may yield innovation and quality advantages through augmentation of human capabilities. This framework implies that competitive advantage mechanisms differ depending on how organizations configure AI-human relationships.

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3.4 Platform Strategies and Ecosystem Dynamics

Platform-based business models and ecosystem strategies represent distinctive contexts for technology adoption and competitive advantage, with implications for how dynamic capabilities operate at ecosystem scale. Recent research has illuminated platform-specific innovation processes, business model evolution patterns, and capability requirements for platform leadership. Wang et al. (2022) identified six platform-specific innovation processes that platform leaders can manage to foster dynamic capabilities and innovation across ecosystems. Their analysis of Taobao revealed that platform leaders orchestrate sensing, seizing, and reconfiguring capabilities not only within their own organizations but across entire ecosystems of complementors and users. Platform-specific processes include ecosystem scanning (sensing emerging needs and technologies across the ecosystem), opportunity framing (defining and communicating opportunities to ecosystem participants), resource mobilization (facilitating resource flows across ecosystem boundaries), innovation coordination (aligning complementor innovations with platform evolution), integration management (ensuring technical and strategic coherence), and value capture design (structuring governance and revenue models).

This research demonstrates that platform strategies require distinctive dynamic capabilities focused on ecosystem orchestration rather than merely internal resource management. Platform business model evolution provides insights into how digital platforms iterate strategies in response to market feedback and competitive dynamics. Platform business model evolution typically follows a pattern of three phases aligned with sensing, seizing, and transformation: initial market entry driven by demand sensing, rapid scaling through network effects, and business model transformation enabled by data centralization and service diversification (Gawer & Cusumano, 2014; Parker et al., 2016). Research on ride-hailing and e-commerce platforms illustrates how platforms leverage data generated through ecosystem interactions to enhance sensing capabilities, which in turn inform business model innovations and strategic repositioning. The centralization of data emerges as a critical platform capability that enables continuous sensing and reconfiguration.

The strategic logic for platform competition differs fundamentally from traditional competitive strategies. Koch and Windsperger (2017) argued that firms should adopt network-centric strategies in digital economies, actively shaping ecosystems and co-creating value to sustain advantage amid digitization-driven disruption. Their framework positions ecosystem orchestration as a core strategic capability, with competitive advantage stemming from the ability to attract and coordinate complementors, establish standards, and govern ecosystem interactions. This network-centric logic implies that technology adoption decisions should consider not only internal capability enhancement but also ecosystem positioning and complementor coordination. Sector-specific platform adoption patterns reveal how industry context shapes platform strategies and capability requirements. Priyanto et al. (2023) found that robotic process automation (RPA) and digital business strategy adoption in banking drives competitiveness, with leadership and culture serving as critical moderators in developing digital advantage in regulated markets. Their research highlights that platform and automation strategies in regulated industries must navigate compliance requirements and risk management constraints, requiring distinctive governance capabilities. The moderating role of leadership and culture suggests that platform success depends not only on technical capabilities but also on organizational readiness and change management.

Industry-specific adoption patterns further illustrate how sector characteristics shape technology-driven competitive dynamics. Liu et al. (2024) demonstrated AI's impacts on dynamic capabilities and competitive outcomes in Chinese construction firms, illustrating industry-specific adoption patterns where AI supports both incremental improvement and strategic repositioning. The construction industry case reveals that AI adoption in asset-intensive, project-based industries enhances sensing through predictive analytics for project risks and opportunities, seizing through optimized resource allocation and scheduling, and reconfiguring through process automation and knowledge management. These sector-specific mechanisms suggest that capability-building priorities should reflect industry characteristics and competitive dynamics. Technology-specific capability requirements have emerged as an important consideration in platform and ecosystem strategies. Noronha et al. (2022) demonstrated that IoT adoption in cleantech lowers transaction costs and increases predictability, suggesting that different technologies produce distinctive disruption patterns and capability requirements. IoT's impact on transaction costs and predictability implies that IoT-enabled platforms can coordinate distributed assets and actors more efficiently than traditional hierarchical structures, creating opportunities for new platform business models in industries characterized by distributed physical assets.

Cross-sectional evidence on performance outcomes reveals that technology-driven competitive advantage depends on coupling technology adoption with organizational capabilities. Chen and Tsou (2007) provided evidence that IT adoption

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improves service innovation and competitive advantage in financial firms, with the strength of these relationships depending on how well IT investments align with innovation processes and customer needs. Empirical studies converge on the finding that operational efficiency, innovation outcomes (both product and process), customer agility, and financial performance improve when digital technologies are assimilated and coupled with absorptive capacity and strategic alignment (Sullivan & Wamba, 2024; Wamba-Taguimdje et al., 2020; Abdul Wahab & Radmehr, 2024; Li et al., 2024).

4. THEORETICAL FRAMEWORK: THE STRATEGIC TECHNOLOGY ADOPTION MODEL (STAM)

Building on the literature synthesis, this section presents an integrated Strategic Technology Adoption Model (STAM) that bridges dynamic capabilities theory with practical technology adoption pathways. The STAM model comprises five sequential yet iterative stages that guide enterprises through the process of strategically adopting AI and digital technologies to build competitive advantage. Figure 1 illustrates the complete STAM model, while Figure 2 presents the Dynamic Capabilities Framework that underpins the model's theoretical logic.

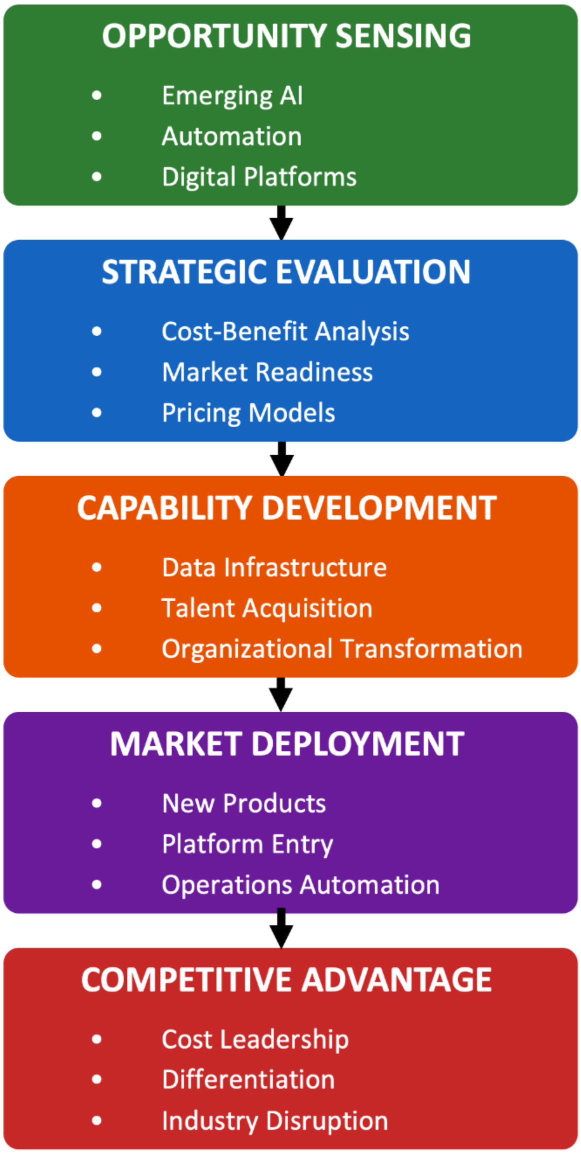

Figure 1. The Strategic Technology Adoption Model (STAM) presents a five-stage framework for strategic technology adoption, encompassing environmental scanning, strategic alignment assessment, capability development, technology integration, and continuous reconfiguration.

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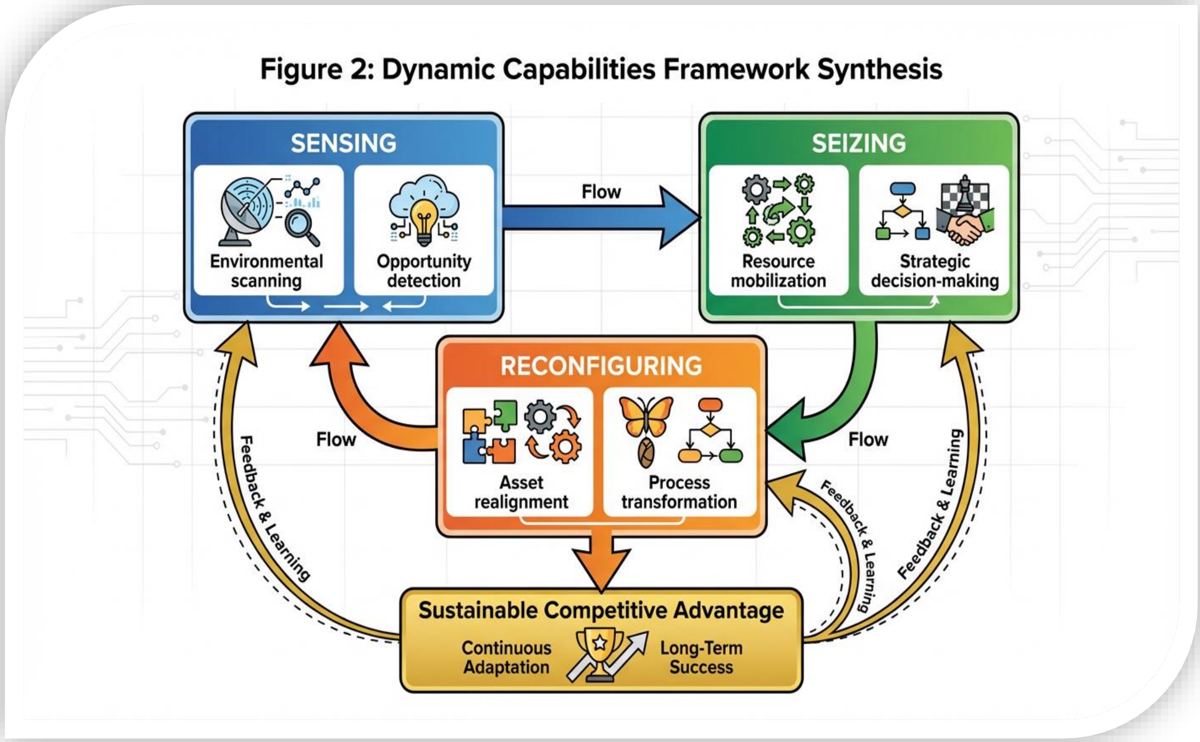

Figure 2. The Dynamic Capabilities Framework synthesizes sensing, seizing, and reconfiguring capabilities with organizational enablers (absorptive capacity, strategic alignment, platform orchestration) and contextual moderators (environmental dynamism, organizational agility, governance structures) to explain technology-driven competitive advantage.

4.1 Stage 1: Environmental Scanning and Sensing

The first stage of the STAM model focuses on environmental scanning and sensing capabilities that enable organizations to identify technological opportunities and threats. Drawing on dynamic capabilities' theory, sensing encompasses the processes and routines through which organizations scan, search, and explore technological and market developments (Teece, 2007). In the context of digital transformation, sensing capabilities must operate at multiple levels: technological trends (emerging AI techniques, platform architectures, digital tools), market dynamics (customer needs, competitor moves, ecosystem evolution), and regulatory developments (data governance, AI ethics, industry standards). Research by Hercheui and Ranjith (2020) demonstrates that AI technologies can enhance sensing capabilities by improving pattern recognition in large datasets, identifying weak signals of market change, and providing predictive analytics regarding future trends. However, technology-enhanced sensing requires organizational routines for interpreting AI-generated insights and translating them into strategic implications. The micro-foundational perspective advanced by Witschel et al. (2023) emphasizes that effective sensing depends on individual skills (data literacy, technological awareness), process routines (environmental scanning protocols, cross-functional information sharing), and structural elements (dedicated sensing units, external partnerships).

Platform leaders demonstrate distinctive sensing approaches that extend beyond firm boundaries. Wang et al. (2022) identified ecosystem scanning as a platform-specific sensing process, wherein platform leaders monitor not only their own market but also complementor innovations, user behavior patterns, and ecosystem health indicators. This ecosystem-level sensing enables platforms to identify opportunities for value creation that span multiple ecosystem participants, informing platform governance and investment decisions. Practical implementation of Stage 1 requires establishing systematic environmental scanning processes, investing in data infrastructure and analytics capabilities, developing cross-functional sensing teams, and creating organizational routines for translating environmental intelligence into strategic discussions. Organizations should assess their current sensing capabilities across technological, market, and regulatory domains, identifying gaps and prioritizing capability-building investments.

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4.2 Stage 2: Strategic Alignment Assessment

The second stage addresses strategic alignment between technology opportunities identified through sensing and the organization's strategic priorities, resources, and capabilities. Strategic alignment has emerged as a critical mediator of technology adoption success, with research consistently demonstrating that technology investments yield superior outcomes when tightly coupled with strategic objectives and organizational capabilities (Jacobs & Pretorius, 2022; Chen & Tsou, 2007). Strategic alignment assessment encompasses multiple dimensions. First, strategic fit evaluation examines whether identified technology opportunities align with the organization's competitive strategy, value proposition, and strategic priorities. Technologies that enable differentiation in strategically important dimensions warrant higher priority than those addressing peripheral activities. Second, resource alignment assessment evaluates whether the organization possesses or can acquire the financial, human, and technical resources necessary to successfully implement and exploit the technology. Third, capability alignment analysis examines whether the organization has or can develop the dynamic capabilities required to sense opportunities, seize them through implementation, and reconfigure resources to sustain advantage.

The systems model proposed by Jacobs and Pretorius (2022) provides a structured approach to alignment assessment, linking technology investments to value creation hierarchies and identifying alignment gaps at strategic, operational, and technical levels. Their framework emphasizes that alignment is not a one-time assessment but a dynamic capability itself, the ability to continuously realign technology investments with evolving strategic priorities. Context-specific considerations shape alignment assessment. Koch and Windsperger (2017) argue that in digital environments, alignment assessment must consider network effects, ecosystem positioning, and value co-creation opportunities beyond traditional firm-centric metrics. For platform strategies, alignment assessment should evaluate how technology investments enhance ecosystem orchestration capabilities and complementor value creation, not merely internal efficiency. Practical implementation of Stage 2 requires developing strategic alignment frameworks that map technology opportunities to strategic priorities, conducting capability gap analyses to identify required capability development, engaging cross-functional leadership in alignment discussions, and establishing governance mechanisms for technology investment decisions. Organizations should create explicit linkages between technology roadmaps and strategic plans, ensuring that adoption decisions reflect strategic priorities rather than technological enthusiasm.

4.3 Stage 3: Capability Development and Preparation

Alignment assessment reveals not only which technologies to pursue but also what the organization lacks. This is the bridge to capability development: Stage 3 addresses the specific gaps in skills, routines, and structures that alignment assessment exposes. Organizations that skip directly from sensing to integration typically discover these gaps mid-implementation, when the cost of remediation is highest. The third stage focuses on building the organizational capabilities necessary to successfully implement and exploit identified technologies. The literature consistently demonstrates that technology adoption success depends critically on capability readiness, with absorptive capacity, organizational agility, and strategic alignment capabilities serving as key mediators of technology-performance relationships (Abdul Wahab & Radmehr, 2024; Wamba-Taguimdje et al., 2020). Capability development must address multiple organizational levels, reflecting the microfoundational perspective advanced by Witschel et al. (2023). At the individual level, capability development encompasses workforce skills, data literacy, technological competencies, and change readiness. Organizations must invest in training, hiring, and knowledge management to build the human capital necessary for technology exploitation. At the process level, capability development involves establishing routines for technology-enabled decision-making, cross-functional collaboration, and continuous learning. At the structural level, capability development requires governance structures, data infrastructure, and organizational designs that support technology integration and exploitation. Absorptive capacity emerges as a particularly critical capability for AI and digital technology adoption. Abdul Wahab and Radmehr (2024) demonstrated that AI assimilation enhances absorptive capacity, which in turn mediates AI's effect on firm performance. Absorptive capacity, comprising acquisition, assimilation, transformation, and exploitation of external knowledge, enables organizations to recognize the value of AI-generated insights, integrate them with existing knowledge, and apply them to commercial ends. Building absorptive capacity requires investments in data practices, analytical skills, and organizational learning routines.

Customer agility represents another key capability identified in recent research. Abdul Wahab and Radmehr (2024) found that customer agility mediates the relationship between AI assimilation and firm performance, suggesting that organizations must develop capabilities to rapidly adjust offerings and interactions based on technology-enabled customer insights.

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Customer agility encompasses sensing customer needs, responding rapidly to those needs, and learning from customer interactions, capabilities that are enhanced by but not automatically created by AI technologies. Platform orchestration capabilities are essential for organizations pursuing platform strategies. Wang et al. (2022) identified specific capabilities that platform leaders must develop: ecosystem scanning, opportunity framing, resource mobilization, innovation coordination, integration management, and value capture design. These capabilities extend beyond traditional organizational boundaries, requiring skills in ecosystem governance, complementor management, and multi-sided market dynamics. Practical implementation of Stage 3 requires conducting comprehensive capability assessments to identify gaps, developing targeted capability-building programs addressing individual, process, and structural levels, investing in data infrastructure and analytical capabilities, establishing governance structures for technology management, and creating organizational learning routines. Organizations should prioritize capability development based on strategic alignment assessment, focusing resources on capabilities most critical for exploiting prioritized technologies.

4.4 Stage 4: Technology Integration and Seizing

The fourth stage addresses technology integration and the seizing of opportunities through implementation. Seizing capabilities encompass the processes through which organizations mobilize resources, make investment decisions, and implement technologies to capture value from identified opportunities (Teece, 2007). In digital contexts, seizing requires not only technical implementation but also business model innovation, process redesign, and organizational change management. Research by Sullivan and Wamba (2024) demonstrates that AI-powered capabilities, automation, analytics, and relational capabilities, enable adaptive response to market changes, which in turn drives performance and innovation outcomes. This finding suggests that technology integration should focus on building these specific capabilities rather than merely deploying technology. Automation capabilities enable efficiency gains and resource reallocation; analytics capabilities enhance decision quality and insight generation; relational capabilities improve customer engagement and ecosystem coordination. The integration methodology outlined by Abuzaid (2024) provides a comprehensive framework for AI integration, encompassing technical infrastructure, data governance, ethical frameworks, and regulatory compliance. This multidimensional approach reflects the complexity of AI integration, which extends beyond technical deployment to encompass organizational, ethical, and institutional considerations. Successful integration requires coordinated attention to data quality and availability, algorithmic transparency and fairness, human-AI interaction design, and governance mechanisms for AI decision-making.

Platform integration presents distinctive challenges and opportunities. Empirical platform studies illustrate how leading platforms integrate technologies to centralize data, enhance network effects, and enable business model innovation (Gawer & Cusumano, 2014; Parker et al., 2016). Platform integration strategies should focus on enhancing ecosystem value creation, strengthening network effects, and building data assets that enable continuous sensing and reconfiguration. The substitution-complementarity framework introduced by Siaw and Ali (2024) highlights strategic choices in technology integration. Organizations must decide whether AI substitutes for or complements human capabilities in each application domain, with implications for workforce strategy, capability development, and competitive positioning. Substitution strategies may yield cost advantages but risk losing tacit knowledge and adaptive capabilities; complementarity strategies may yield innovation advantages but require more complex human-AI coordination. Practical implementation of Stage 4 requires developing detailed integration roadmaps with clear milestones and success metrics, establishing cross-functional integration teams combining technical and business expertise, implementing robust data governance and ethical frameworks, designing human-AI interaction models that leverage complementarities, and establishing feedback mechanisms to monitor integration progress and outcomes. Organizations should adopt agile implementation approaches that enable rapid iteration and learning.

4.5 Stage 5: Continuous Reconfiguration and Transformation

Integration is not the endpoint. Technologies degrade in competitive value as rivals imitate, customer expectations shift, and the frontier advances. Stage 5 closes the loop: reconfiguration feeds market feedback and performance data back into sensing (Stage 1), creating an iterative cycle rather than a one-shot adoption event. This feedback mechanism is what distinguishes sustainable competitive advantage from a temporary performance spike.

The fifth stage addresses continuous reconfiguration and transformation capabilities that enable organizations to sustain competitive advantage in dynamic environments. Reconfiguring capabilities encompass the processes through which

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organizations realign resources, restructure operations, and transform business models in response to technological and market changes (Teece, 2007). In digital contexts, reconfiguration must be continuous rather than episodic, reflecting the rapid pace of technological change and market evolution. Research by Wamba-Taguimdje et al. (2020) demonstrates that AI capabilities improve organizational performance by reconfiguring process-oriented dynamic capabilities, enabling continuous process innovation and resource reallocation. This finding suggests that technology-enabled reconfiguration should focus on building adaptive processes that can evolve in response to AI-generated insights and changing market conditions. The microfoundational perspective emphasizes that reconfiguration requires interventions at individual, process, and structural levels. Witschel et al. (2023) identified specific responses necessary for successful digital business model innovation: individual-level responses (skill development, mindset shifts), process-level responses (routine redesign, decision-making changes), and structural responses (organizational redesign, governance evolution). Effective reconfiguration addresses all three levels in coordinated fashion. Platform reconfiguration demonstrates distinctive patterns. Leading platforms continuously reconfigure business models, service offerings, and ecosystem governance in response to market feedback and competitive dynamics (Parker et al., 2016). Platform reconfiguration leverages data generated through ecosystem interactions to inform strategic pivots, with centralized data serving as a key asset enabling rapid sensing and response.

The relationship between reconfiguration and strategic alignment is dynamic and reciprocal. Jacobs and Pretorius (2022) emphasize that reconfiguration must maintain strategic alignment even as strategies evolve, requiring continuous realignment of technology investments with shifting strategic priorities. This dynamic alignment capability enables organizations to sustain coherence between technology infrastructure and strategic direction despite ongoing transformation. Practical implementation of Stage 5 requires establishing continuous monitoring and feedback systems to track technology performance and market changes, creating organizational routines for periodic strategic reassessment and realignment, building organizational agility and change management capabilities, investing in modular and flexible technology architectures that enable rapid reconfiguration, and fostering organizational cultures that embrace continuous learning and adaptation. Organizations should view reconfiguration not as a discrete project but as an ongoing capability that enables sustained competitive advantage.

5. SYNTHESIS AND DISCUSSION

5.1 Mediating Mechanisms: Absorptive Capacity and Organizational Agility

The synthesis of contemporary research reveals that the relationship between technology adoption and competitive advantage is mediated by specific organizational capabilities, with absorptive capacity and organizational agility emerging as particularly critical mediators. These mediating mechanisms explain why technology investments alone prove insufficient and why capability development must accompany technology adoption. Absorptive capacity, the ability to recognize, assimilate, and apply external knowledge, serves as a fundamental mediator of technology-performance relationships. Abdul Wahab and Radmehr (2024) demonstrated that AI assimilation enhances absorptive capacity, which in turn mediates AI's positive effect on firm performance. This mediating role reflects a critical insight: AI systems generate vast amounts of data and insights, but organizational value depends on the ability to interpret, integrate, and act upon those insights. Organizations with strong absorptive capacity can rapidly translate AI-generated patterns into strategic actions, while those with weak absorptive capacity may possess powerful AI systems that generate underutilized insights. The components of absorptive capacity, acquisition, assimilation, transformation, and exploitation, map directly onto the STAM model stages. Acquisition capabilities enable effective environmental scanning (Stage 1), assimilation capabilities support strategic alignment assessment (Stage 2), transformation capabilities underpin capability development (Stage 3), and exploitation capabilities drive technology integration and reconfiguration (Stages 4-5). This mapping suggests that absorptive capacity development should be explicitly integrated into technology adoption strategies, with targeted investments in each component.

Organizational agility represents a second critical mediator, encompassing the ability to sense and respond rapidly to market changes. Abdul Wahab and Radmehr (2024) found that customer agility mediates the AI-performance relationship, with organizational agility moderating the strength of mediation. Sullivan and Wamba (2024) identified adaptive response to market changes as a key mechanism through which AI-powered capabilities influence performance and innovation outcomes. These findings converge on the insight that technology-enabled sensing and analytics yield competitive advantage only when organizations can rapidly translate insights into market actions. The relationship between absorptive capacity and organizational agility is complementary and reinforcing. Absorptive capacity enables organizations to recognize and interpret market signals, while organizational agility enables rapid response to those signals. Together, these capabilities create a dynamic feedback loop: agile responses generate market feedback that enhances absorptive capacity, while enhanced absorptive capacity identifies opportunities for agile action. Technology investments that strengthen both capabilities yield multiplicative rather than merely additive effects. Process-oriented dynamic capabilities serve as additional mediators linking technology adoption to performance outcomes. Wamba-Taguimdje et al. (2020) synthesized evidence demonstrating that AI capabilities improve organizational performance by reconfiguring process-oriented dynamic capabilities. This finding highlights that technology effects are channeled through process innovation and operational transformation rather than directly impacting performance. Organizations must therefore focus technology integration efforts on process redesign and capability reconfiguration rather than merely automating existing processes.

5.2 Moderating Factors: Context, Leadership, and Governance

While absorptive capacity and organizational agility mediate technology-performance relationships, contextual factors moderate the strength and nature of these relationships. Understanding these moderating factors is essential for tailoring technology adoption strategies to specific organizational and environmental contexts. Environmental dynamism and hostility emerge as important moderators of technology effects. Sullivan and Wamba (2024) found that environmental hostility and dynamism moderate the relationships between adaptive response capabilities and performance outcomes, with stronger effects in more dynamic and hostile environments. This moderating effect reflects a fundamental principle: the value of adaptive capabilities increases with environmental uncertainty and competitive intensity. In stable, benign environments, adaptive capabilities confer less advantage because strategic positions can be sustained through operational excellence and incremental improvement.

In dynamic, hostile environments, adaptive capabilities become essential for survival and advantage. Organizational agility moderates the strength of mediating relationships between technology adoption and performance. Abdul Wahab and Radmehr (2024) demonstrated that organizational agility moderates the mediation of absorptive capacity and customer agility in the AI-performance relationship. Organizations with high baseline agility extract greater value from AI investments because they can more rapidly translate AI-generated insights into market actions. This moderating effect suggests that agility-building investments may yield higher returns than technology investments for organizations with low baseline agility. Leadership and organizational culture moderate technology adoption success across multiple dimensions. Priyanto et al. (2023) found that leadership and culture serve as critical moderators in developing digital advantage in banking, with strong leadership and supportive culture amplifying the competitive effects of RPA and digital business strategy adoption. Leadership influences technology adoption through resource allocation decisions, change management effectiveness, and the creation of organizational climates that support experimentation and learning. Culture shapes technology adoption through employee receptivity to change, willingness to experiment with new tools, and norms regarding data-driven decision-making.

Governance structures and ethical frameworks moderate AI adoption outcomes by shaping how AI systems are designed, deployed, and monitored. Siaw and Ali (2024) highlighted ethical and governance implications of AI-human substitution and complementarity choices, noting that governance structures influence whether AI enhances or undermines organizational capabilities. Robust governance frameworks ensure that AI systems align with organizational values, comply with regulatory requirements, and maintain human oversight of critical decisions. Weak governance may lead to algorithmic bias, ethical violations, or loss of human expertise, undermining rather than enhancing competitive advantage. Industry context moderates technology adoption patterns and capability requirements. Liu et al. (2024) illustrated industry-specific adoption patterns in construction, where AI supports both incremental improvement and strategic repositioning.

Noronha et al. (2022) demonstrated sector-specific mechanisms in cleantech, where IoT adoption lowers transaction costs and increases predictability. These sector-specific patterns suggest that capability-building priorities and adoption strategies should reflect industry characteristics, competitive dynamics, and regulatory environments. Regulatory context moderatestechnology adoption through compliance requirements and risk management constraints. Priyanto et al. (2023) highlighted that platform and automation strategies in regulated industries must navigate compliance requirements, requiring distinctive governance capabilities. Gupta et al. (2024) emphasized that enterprise AI produces value when aligned with regulation and risk controls, suggesting that regulatory context shapes both adoption strategies and capability requirements.

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5.3 Platform Orchestration and Ecosystem-Level Capabilities

Platform strategies and ecosystem dynamics introduce distinctive considerations for technology adoption and competitive advantage, with implications for how dynamic capabilities operate beyond firm boundaries. Platform orchestration capabilities enable organizations to coordinate value creation across ecosystems of complementors, suppliers, and customers, representing an extension of traditional dynamic capabilities. Wang et al. (2022) identified six platform-specific innovation processes that constitute platform orchestration capabilities: ecosystem scanning, opportunity framing, resource mobilization, innovation coordination, integration management, and value capture design.

These processes map onto the sensing-seizing-reconfiguring framework but operate at ecosystem rather than firm level. These ecosystem-level processes described in detail in Section 3.4 map onto the sensing-seizing-reconfiguring logic but introduce a fundamental tension for the STAM model. Firm-level STAM stages assume the organization controls its own capability trajectory. Platform orchestration requires coordinating capability development across independent actors with their own priorities. This creates a trade-off: a platform leader may need to slow its own integration (Stage 4) to let complementors build compatible capabilities (their Stage 3). Similarly, ecosystem-level sensing requires data infrastructure investments that benefit the whole ecosystem, not just the focal firm. This collective action problem absent from firm-level dynamic capabilities theory.

Ecosystem scanning extends sensing beyond the focal firm to monitor complementor innovations and user behavior patterns. Opportunity framing translates ecosystem-level sensing into actionable opportunities for multiple ecosystem participants. Resource mobilization facilitates resource flows across ecosystem boundaries. Innovation coordination aligns complementor innovations with platform evolution. Integration management ensures technical and strategic coherence across ecosystem components. Value capture design structures governance and revenue models to sustain ecosystem participation.

The development of platform orchestration capabilities requires distinctive investments and organizational structures. Platform leaders must build capabilities in ecosystem governance, complementor management, multi-sided market dynamics, and data-driven ecosystem optimization. These capabilities extend beyond traditional organizational boundaries, requiring skills in negotiation, standard-setting, and value distribution that differ from capabilities required for vertically integrated operations. Data centralization emerges as a critical platform capability that enables continuous sensing and reconfiguration. Platform case research illustrates how leading platforms leverage data generated through ecosystem interactions to enhance sensing capabilities, inform business model innovations, and enable strategic repositioning (Gawer & Cusumano, 2014). Centralized data provides platforms with informational advantages over ecosystem participants, enabling superior sensing of market trends, user preferences, and complementor performance.

This informational advantage translates into enhanced seizing and reconfiguring capabilities, as platforms can identify and respond to opportunities more rapidly than individual ecosystem participants. Network effects moderate the value of platform orchestration capabilities. Koch and Windsperger (2017) argue that in digital environments characterized by strong network effects, competitive advantage stems from the ability to attract and coordinate complementors, establish standards, and govern ecosystem interactions. Platform orchestration capabilities become more valuable as network effects strengthen, because the coordination challenges and opportunities increase with ecosystem size and complexity. The relationship between platform orchestration and traditional dynamic capabilities is complementary. Effective platform strategies require both internal dynamic capabilities (to sense, seize, and reconfigure the platform firm's own resources) and ecosystem-level orchestration capabilities (to coordinate sensing, seizing, and reconfiguring across the ecosystem). Organizations pursuing platform strategies must therefore develop capabilities at both levels, with explicit attention to how internal and ecosystem-level capabilities interact and reinforce each other.

5.4 AI-Human Complementarity and Capability Substitution

The emergence of artificial intelligence introduces fundamental questions regarding the relationship between human and machine capabilities, with significant implications for how organizations build and deploy dynamic capabilities. The substitution-complementarity framework advanced by Siaw and Ali (2024) provides a theoretical lens for understanding these relationships and their strategic implications. Siaw and Ali (2024) theorized that organizations face strategic choices regarding whether AI substitutes for or complements human intelligence across sensing, seizing, and reconfiguring processes. In sensing, AI can substitute for human pattern recognition in large datasets or complement human judgment by

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providing data-driven insights that inform intuitive decision-making. In seizing, AI can substitute for human decision-making in routine resource allocation or complement human strategic judgment by providing decision support and scenario analysis. In reconfiguring, AI can substitute for human process execution through automation or complement human creativity by enabling rapid prototyping and experimentation.

The choice between substitution and complementarity carries significant implications for capability development and competitive advantage. Substitution strategies may yield cost advantages through automation and efficiency gains, but risk losing tacit knowledge, adaptive capabilities, and the ability to handle novel situations that fall outside AI training data. Complementarity strategies may yield innovation and quality advantages through augmentation of human capabilities, but require more complex human-AI coordination and may realize cost savings more slowly. Empirical evidence suggests that complementarity strategies often yield superior outcomes in dynamic, uncertain environments. Hercheui and Ranjith (2020) found that AI contributes to dynamic capabilities by enhancing rather than replacing human sensing, seizing, and transforming activities, with interpretive skills and organizational learning necessary to translate AI outputs into strategic actions. This finding suggests that AI's greatest value lies in augmenting human capabilities rather than substituting for them, particularly in strategic domains requiring judgment, creativity, and adaptation to novel situations.

The micro-foundational perspective highlights that substitution-complementarity choices must be made at individual, process, and structural levels. At the individual level, organizations must decide which tasks AI will automate versus augment, with implications for workforce skills and roles. At the process level, organizations must design workflows that effectively integrate human and AI contributions, establishing clear handoffs and feedback loops. At the structural level, organizations must create governance mechanisms that maintain human oversight of AI systems while enabling AI to enhance human decision-making. Ethical and governance considerations shape substitution-complementarity choices. Siaw and Ali (2024) noted that substitution strategies raise concerns regarding workforce displacement, loss of human expertise, and accountability for AI decisions. Complementarity strategies require governance frameworks that clarify human-AI roles, maintain human oversight of critical decisions, and ensure that AI systems augment rather than undermine human judgment. Organizations must therefore consider ethical implications and governance requirements when making substitution-complementarity choices. The dynamic nature of AI capabilities suggests that substitution-complementarity choices should be revisited periodically. As AI capabilities advance, tasks that currently require human-AI complementarity may become candidates for substitution, while new domains may emerge where AI can complement human capabilities in novel ways. Organizations should therefore view substitution-complementarity choices not as static decisions but as dynamic strategies that evolve with AI capabilities and organizational learning.

6. IMPLICATIONS FOR THEORY AND PRACTICE

6.1 Theoretical Contributions

This synthesis makes three principal contributions to theory at the intersection of dynamic capabilities, technology adoption, and competitive advantage.

First, the STAM model offers an integrative process framework with formal, testable propositions—a feature absent from prior models such as Vial (2019) and Warner and Wäger (2019). By mapping five iterative stages onto the sensing-seizing-reconfiguring logic and deriving twelve propositions that specify mediating and moderating conditions, the STAM model provides a falsifiable architecture for future empirical work. Its stage structure enables researchers to examine adoption processes longitudinally and practitioners to diagnose precisely where and why adoption efforts stall.

Second, the microfoundational specification advanced through synthesis of recent research (particularly Witschel et al., 2023) moves beyond abstract capability constructs to identify concrete organizational elements at individual, process, and structural levels. Importantly, the synthesis reveals that these levels are not independent: individual skills without supporting process routines remain latent, and process redesign without structural governance remains fragile.

Third, the paper extends dynamic capabilities theory in two directions simultaneously: outward to ecosystem-level orchestration (building on Wang et al., 2022) and inward to AI-human role configuration (building on Siaw & Ali, 2024). The ecosystem extension recognizes that competitive advantage increasingly depends on orchestrating capabilities across firm boundaries. The AI-human substitution-complementarity dimension adds a layer of strategic choice unique to the current technological moment: organizations must decide not merely whether to adopt AI but how to configure human and machine roles across each dynamic capability, with implications for workforce strategy, governance, and the sustainability of competitive advantage.

6.2 Managerial Implications

The synthesis yields several actionable implications for managers responsible for technology adoption and digital transformation initiatives. First, technology adoption strategies should explicitly address capability development alongside technology implementation. The consistent finding that absorptive capacity, organizational agility, and strategic alignment mediate technology-performance relationships implies that capability-building investments may yield higher returns than technology investments alone. Managers should conduct capability assessments before major technology investments, identifying gaps and developing targeted capability-building programs. Second, strategic alignment should be treated as a dynamic capability requiring continuous attention rather than a one-time assessment. The finding that alignment mediates technology adoption success (Jacobs & Pretorius, 2022; Chen & Tsou, 2007) suggests that organizations should establish governance mechanisms for ongoing alignment assessment and realignment. Technology roadmaps should be explicitly linked to strategic plans, with periodic reviews to ensure continued alignment as strategies and technologies evolve. Third, microfoundational interventions at individual, process, and structural levels should be coordinated rather than pursued in isolation. The microfoundational perspective (Witschel et al., 2023) implies that successful digital transformation requires interventions addressing workforce skills, decision routines, and organizational structures simultaneously.

Managers should design transformation programs that coordinate interventions across these levels, recognizing that individual skill development without process redesign or structural change will yield limited results. Fourth, platform strategies require distinctive capability-building investments focused on ecosystem orchestration. Organizations pursuing platform business models should develop capabilities in ecosystem scanning, complementor management, multi-sided market dynamics, and data-driven ecosystem optimization (Wang et al., 2022). These capabilities differ from those required for vertically integrated operations and require dedicated investment and organizational attention. Fifth, AI adoption strategies should explicitly address substitution-complementarity choices and their implications for workforce strategy and governance.

The substitution-complementarity framework (Siaw & Ali, 2024) implies that organizations should make deliberate choices regarding where AI substitutes for versus complements human capabilities, considering both efficiency and innovation implications. Complementarity strategies require investments in human-AI interaction design, workforce upskilling, and governance frameworks that maintain human oversight while enabling AI augmentation. Sixth, contextual factors should inform adoption strategy tailoring. The moderating effects of environmental dynamism, organizational agility, leadership, and industry context suggest that adoption strategies should be customized to organizational and environmental circumstances. Organizations in dynamic, hostile environments should prioritize adaptive capabilities and agile implementation approaches. Organizations in regulated industries should invest in governance capabilities and compliance frameworks. Organizations with weak baseline agility should prioritize agility-building before major technology investments.

6.3 Policy and Governance Considerations

The synthesis highlights several policy and governance considerations relevant to technology adoption and digital transformation at organizational and societal levels. First, governance frameworks for AI adoption should address ethical implications of substitution-complementarity choices, ensuring that AI systems augment rather than inappropriately replace human judgment in critical domains. Policymakers and organizational leaders should establish guidelines regarding appropriate domains for AI substitution versus complementarity, with particular attention to decisions affecting human welfare, safety, and rights. Second, the substitution-complementarity choices at Stage 4 (Proposition 6) raise governance questions that current regulatory frameworks do not adequately address. Policymakers should develop sector-specific guidelines specifying where AI-human complementarity should be mandated in high-stakes domains like healthcare diagnostics and financial risk assessment, versus where full substitution may be appropriate.

Policies aimed at promoting digital transformation should therefore address capability development alongside technology diffusion, supporting investments in workforce skills, organizational learning, and absorptive capacity. Educational institutions and workforce development programs should emphasize capabilities required for technology exploitation, including data literacy, analytical skills, and change management competencies. Third, platform governance frameworks should address ecosystem-level dynamics and power asymmetries between platform leaders and ecosystem participants. The finding that platform leaders leverage data centralization and orchestration capabilities to gain informational and strategic advantages (Gawer & Cusumano, 2014; Parker et al., 2016; Wang et al., 2022) raises questions regarding fair value distribution and ecosystem sustainability.

Policymakers should consider governance mechanisms that ensure ecosystem participants receive fair value shares and maintain sufficient autonomy to invest in innovation. Fourth, data governance frameworks should balance the value of data centralization for sensing and reconfiguring capabilities against privacy, security, and competition concerns. The critical role of data in enabling dynamic capabilities (particularly sensing) suggests that data access and portability policies significantly affect competitive dynamics. Policymakers should design data governance frameworks that enable capability development while protecting individual privacy and preventing anticompetitive data concentration.

6.4 Limitations

Several limitations of this review should be acknowledged. First, while the structured search protocol enhances transparency, the review remains bounded by the databases searched and the search terms employed; relevant studies published in non-English journals or using different terminology may have been omitted. Second, the STAM model and its propositions are derived from narrative synthesis rather than meta-analytic methods, meaning that the strength of reported relationships cannot be quantified with statistical precision. Third, the propositions remain untested and should be treated as theoretical conjectures awaiting empirical validation. Fourth, the review draws primarily on studies from technology-intensive and service-oriented industries; the applicability of the STAM framework to primary industries, public sector organizations, and non-profit contexts remains an open question. Fifth, rapid advances in generative AI and large language models since the literature search window may introduce new adoption dynamics not fully captured in the reviewed studies.

7. CONCLUSION AND FUTURE RESEARCH DIRECTIONS

This paper has synthesized contemporary research on strategic technology adoption through the lens of dynamic capabilities theory, developing an integrated Strategic Technology Adoption Model (STAM) that bridges theoretical frameworks with practical implementation pathways. The synthesis reveals that technology-driven competitive advantage depends not on technology adoption alone but on organizational capabilities that enable environmental scanning, opportunity capture, and resource reconfiguration. Absorptive capacity, organizational agility, and strategic alignment emerge as critical mediators of technology-performance relationships, while environmental dynamism, leadership, governance, and industry context moderate these relationships. The STAM model provides a structured framework for enterprises to strategically adopt AI and digital technologies, encompassing five stages: environmental scanning and sensing, strategic alignment assessment, capability development and preparation, technology integration and seizing, and continuous reconfiguration and transformation. The model emphasizes that successful digital transformation requires coordinated attention to microfoundational elements at individual, process, and structural levels, with explicit linkage of technology investments to capability development and strategic priorities.

Future Research Agenda

Several directions for future research emerge from this synthesis. First, longitudinal research examining how organizations progress through STAM stages would provide valuable insights into adoption dynamics, capability development trajectories, and the temporal relationships between capability building and performance outcomes. Such research could identify critical junctures where adoption efforts commonly fail and interventions that facilitate successful progression.

Second, comparative research examining substitution versus complementarity strategies for AI-human relationships would illuminate the conditions under which each approach yields superior outcomes. Research should examine how substitution-complementarity choices affect capability development, innovation outcomes, workforce dynamics, and long-term competitive advantage across different organizational and environmental contexts.

Third, ecosystem-level research examining how platform orchestration capabilities develop and how value is created and distributed across digital ecosystems would extend dynamic capabilities theory to multi-organizational contexts. Such research should examine governance mechanisms that sustain ecosystem participation, innovation coordination processes that align complementor investments with platform evolution, and data strategies that balance platform sensing capabilities with ecosystem participant autonomy.

Fourth, sector-specific research examining how industry characteristics shape technology adoption patterns, capability requirements, and competitive dynamics would enable more precise tailoring of adoption strategies. Research should examine how regulatory environments, asset intensity, customer characteristics, and competitive structures influence optimal adoption pathways and capability-building priorities.

In conclusion, strategic technology adoption in the age of AI and digital innovation requires more than technological sophistication; it demands organizational capabilities that enable continuous sensing, seizing, and reconfiguring in dynamic environments. The STAM model and Dynamic Capabilities Framework presented in this paper provide integrated perspectives for understanding and managing this complex challenge, with implications for theory, practice, and policy. As digital technologies continue to evolve and reshape competitive landscapes, the capabilities to strategically adopt and exploit these technologies will increasingly determine which organizations thrive and which struggle in the digital economy.

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