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AI Capability and SME Business Model Innovation: An Integrative Review

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Abstract

This study examines how artificial intelligence (AI) capability is associated with business model innovation and competitive advantage in small and medium-sized enterprises (SMEs), distinguishing AI-related resources from organizational capabilities and contextual conditions. An integrative literature review synthesized 32 scholarly publications issued between 2007 and 2026, selected for their relevance to AI capability, dynamic capabilities, business model innovation, and firm performance. A theory-guided thematic synthesis organized the evidence into resource and capability foundations, organizational conversion mechanisms, boundary conditions, and strategic outcomes. The reviewed literature identifies technological infrastructure, data resources, and human expertise as important foundations of AI capability, while leadership, organizational learning, governance, and data-driven culture shape the organizational utilization of these resources. Business model innovation is identified as a potential intermediary mechanism involving changes in value proposition, value creation and delivery, and value capture. Environmental dynamism, sustainability orientation, organizational adaptability, and external integration influence the applicability of these relationships. The review develops a capability-to-business-model pathway that distinguishes AI resource foundations, capability utilization, organizational conversion processes, business model changes, and context-dependent competitive outcomes. Its contribution lies in clarifying construct boundaries and integrating previously separated explanations of AI-related organizational value in SMEs. The findings support differentiated, resource-sensitive approaches to AI adoption, although the conceptual synthesis does not establish causal effects or uniform performance benefits across firms.

Keywords: AI capability, business model innovation, dynamic capabilities, SMEs, competitive advantage.



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INTRODUCTION

Digital transformation has altered the competitive environment by increasing the strategic importance of organizational capabilities in developing, integrating, and utilizing digital technologies. For small and medium-sized enterprises (SMEs), this development presents opportunities for operational improvement, market expansion, and business model renewal while exposing persistent constraints in financial resources, technological infrastructure, specialist expertise, and managerial capacity. The strategic significance of digital transformation extends beyond technological adoption because organizational value depends on the ability to integrate digital resources into business processes, managerial decisions, and competitive strategies. Research on digital transformation has emphasized strategic renewal, resource reconfiguration, and organizational capability development as fundamental processes through which firms respond to technological change (Vial, 2019; Warner & Wäger, 2019; Verhoef et al., 2021). These considerations are particularly relevant to SMEs, whose limited resource portfolios increase the importance of selecting, combining, and utilizing technological investments to support innovation and sustained competitive performance.

Artificial intelligence (AI) has become an important component of digital transformation because its applications extend beyond routine automation to predictive analysis, knowledge recombination, customer intelligence, operational optimization, and market opportunity identification. AI technologies

can support organizational decision-making and improve information-processing efficiency, but their acquisition does not independently establish the organizational capacity required to generate strategic value. The realization of AI-related benefits depends on the availability of reliable data, appropriate technological infrastructure, specialized human expertise, and processes capable of incorporating analytical outputs into organizational activities (Mikalef & Gupta, 2021; Wamba-Taguimdje et al., 2020; Enholm et al., 2022). A distinction is consequently necessary between possessing AI-related resources and developing the organizational capability to deploy those resources effectively. This distinction is especially significant for SMEs because technological investments frequently occur under conditions of limited absorptive capacity, organizational specialization, and access to external technical support.

AI capability is conceptualized in this study as the organizational capacity to integrate, mobilize, and apply AI-related technological infrastructure, data resources, and human expertise to generate analytical intelligence and support organizational decisions and activities. AI resources constitute the underlying technological, informational, and human assets available to the firm, whereas AI capability concerns the coordinated utilization of these assets through AI-enabled analytical and operational processes. Complementary organizational capabilities, including adaptive leadership, organizational learning, managerial coordination, and resource reconfiguration, influence the effectiveness with which AI capability is translated into strategic action. Governance arrangements, established routines, and data-driven organizational culture provide supporting conditions for the responsible and consistent utilization of AI-generated information. Business model innovation and competitive performance are treated as potential outcomes rather than constitutive elements of AI capability. This conceptual differentiation builds on the multidimensional treatment of AI capability developed by Mikalef and Gupta (2021) and the organizational perspective on AI-related business value discussed by Enholm et al. (2022). It also establishes analytical boundaries among resources, capabilities, organizational mechanisms, and strategic outcomes that are necessary for examining AI-enabled transformation in SMEs.

Dynamic capabilities theory provides a theoretical foundation for explaining how AI capability interacts with organizational adaptation and business transformation. Dynamic capabilities refer to the organizational capacity to sense environmental developments, seize emerging opportunities, and reconfigure resources in response to changing technological and market conditions (Teece, 2007, 2018). AI capability can contribute to these activities by expanding analytical capacity, improving the recognition of market patterns, and supporting knowledge-based decisions. Its strategic contribution nevertheless depends on organizational processes that translate analytical information into resource allocation, experimentation, and operational adjustment. The automation–augmentation paradox further indicates that organizational outcomes are influenced by the distribution of responsibilities between algorithmic systems and human decision-makers (Raisch & Krakowski, 2021). AI capability and dynamic capabilities are consequently treated as related but conceptually distinct constructs: the former concerns the organizational application of AI-related resources, while the latter concerns broader organizational processes of adaptation and resource reconfiguration. Their interaction provides a theoretical explanation for differences in the organizational utilization of similar technological resources.

Business model innovation constitutes a relevant organizational mechanism through which AI capability may become associated with competitive advantage. A business model describes the configuration of activities through which an organization creates, delivers, and captures value, while business model innovation concerns substantive modifications to the architecture of those activities (Zott et al., 2011; Clauss, 2017; Foss & Saebi, 2017). AI applications may support changes in value propositions through customer segmentation, personalized offerings, and predictive services. They may also influence value creation and delivery through process automation, operational coordination, and intelligent customer interactions, while data-supported pricing, revenue optimization, and digital service arrangements provide potential mechanisms for modifying value capture. These developments are analytically distinct from improvements in the efficiency of existing activities because business model innovation concerns changes in the organization of value-generating processes and relationships. For SMEs, the conversion of AI capability into business model innovation requires attention to the compatibility between technological possibilities, organizational resources, customer requirements, and commercial arrangements.

Empirical research provides evidence of the organizational mechanisms associated with AI-enabled business model transformation. Ghosh (2024) identifies organizational adaptability and leadership as relevant factors in developing AI capabilities for data-driven business model innovation. Fosso Wamba et al. (2024) demonstrate the mediating role of data-driven culture in the relationship between AI capability and firm performance, indicating that the organizational use of analytical information constitutes an important element of AI-related value realization. Shao et al. (2026) report a mediating relationship involving business model innovation between AI capability and enterprise competitive advantage. These findings suggest that technological resources, organizational conversion processes, and business model changes represent distinct analytical elements in explanations of competitive performance. They do not establish that equivalent relationships operate uniformly across SMEs because organizational characteristics, resource availability, industrial conditions, and technological maturity may influence the direction and strength of the reported associations. A coherent conceptual explanation requires the integration of these mechanisms while maintaining distinctions between empirically documented relationships and theoretically inferred pathways.

Existing literature reviews have established important foundations for understanding the organizational implications of AI, although their analytical priorities differ from the specific capability-to-business-model relationship examined in this study. Enholm et al. (2022) synthesize research on AI and business value, emphasizing the organizational conditions and mechanisms associated with value realization. Haefner et al. (2021) examine AI in innovation management and develop a framework for understanding its implications for innovation processes, while Mariani et al. (2023) consolidate research on AI and innovation and identify conceptual developments and directions for further investigation. Research on the strategic application of AI has also examined its relationships with managerial decision-making, competitive strategy, and organizational transformation (Borges et al., 2021; Keding, 2021). These contributions clarify the broader technological, organizational, innovative, and strategic implications of AI. However, their different analytical orientations leave limited integration of the resource foundations of AI capability, the complementary organizational processes involved in capability utilization, the specific dimensions of business model innovation, and the contextual conditions influencing competitive outcomes in resource-constrained SMEs.

A further limitation in the existing knowledge base concerns the conceptual treatment of technological resources, organizational capabilities, and transformation mechanisms. Studies addressing organizational creativity, digital transformation, leadership, data-driven culture, business-process improvement, innovation resilience, and entrepreneurship offer relevant but partially differentiated explanations of AI-related organizational outcomes (Haefner et al., 2021; Mariani et al., 2023; Zhang et al., 2024; Singh et al., 2026). Some explanations emphasize the resources required to implement AI, while others concentrate on organizational characteristics that facilitate implementation or on performance outcomes associated with AI utilization. The relationships among these elements are not consistently organized according to their respective conceptual functions. In particular, the distinction between AI capability as the capacity to utilize technological and informational resources, complementary organizational capabilities as mechanisms supporting strategic adaptation, and business model innovation as a potential intermediary outcome remains insufficiently integrated for the SME setting. This limitation restricts the explanatory precision of existing conceptual models and complicates the identification of organizational processes through which AI-related investments may contribute to competitive advantage. The present study addresses this gap through an integrative synthesis that organizes these relationships into an explicitly differentiated analytical structure rather than treating AI capability as an unrestricted collection of technological and organizational attributes.

Contextual variation further complicates the relationship between AI capability and strategic outcomes. Environmental dynamism, resource constraints, organizational maturity, industry characteristics, and external knowledge integration may influence the extent to which AI-related resources can be incorporated into business activities and converted into business model changes. Recent research associates AI capability with sustainable firm performance, innovative work behavior, green innovation, business-process improvement, and organizational resilience, while also identifying differences associated with organizational and environmental conditions (Farmanesh et al., 2025; Shahid et al., 2026; Sharma & Dang, 2026). Ciampi et al. (2022) further demonstrate the relevance of the co-evolution of digital technologies and sustainable business models for understanding organizational performance. These findings indicate that sustainability orientation and environmental

conditions warrant analytical consideration alongside technological and managerial factors. For SMEs, external partnerships, governance arrangements, learning capacity, and the availability of complementary resources may affect the feasibility and effectiveness of AI-enabled business model experimentation. Such conditions are not assumed to produce uniform effects across organizations but are examined as potential influences on the relationships between AI capability, business model innovation, and competitive outcomes.

The study is guided by three research questions. First, what technological, informational, and human resource dimensions constitute the foundations of AI capability in SMEs, and how can these dimensions be distinguished from complementary organizational capabilities? Second, through which organizational conversion mechanisms is AI capability associated with innovation in value proposition, value creation and delivery, and value capture? Third, which organizational and environmental conditions influence the relationships among AI capability, business model innovation, and competitive outcomes in SMEs? These questions establish a common analytical basis for examining the relevant literature and distinguishing the principal constructs, mechanisms, and contextual relationships. They also provide a structure for comparing findings across information systems, strategic management, innovation research, entrepreneurship, and digital transformation studies without assuming that the available empirical evidence supports identical relationships in all organizational settings.

This study employs an integrative literature review to synthesize theoretical and empirical evidence concerning AI capability, complementary organizational capabilities, business model innovation, and competitive advantage in SMEs. Its principal contribution is the development of a capability-to-business-model pathway comprising four analytically connected elements: AI resource and capability foundations, organizational conversion mechanisms, business model innovation, and context-dependent strategic outcomes. The proposed pathway distinguishes the integration and utilization of AI-related resources from the organizational processes through which analytical capacity may support the reconfiguration of value propositions, value creation and delivery activities, and value-capture arrangements. Environmental dynamism, organizational adaptability, sustainability orientation, and external integration are incorporated according to their potential roles as complementary capabilities or contextual conditions rather than being treated interchangeably with AI capability. This framework extends existing reviews by connecting previously differentiated research streams within an SME-oriented explanation of technological capability utilization and business model transformation. Its theoretical contribution lies in clarifying the conceptual boundaries and proposed relationships among the principal constructs, while its practical relevance concerns the identification of organizational capabilities and conversion processes associated with different approaches to AI-enabled business model development. The resulting synthesis provides a conceptual basis for subsequent empirical examination of the proposed relationships across industries, institutional environments, and levels of SME technological maturity.

RESEARCH METHODS

This study employed an integrative literature review design to synthesize theoretical and empirical evidence concerning artificial intelligence (AI) capability, business model innovation, dynamic capabilities, and competitive advantage in small and medium-sized enterprises (SMEs). The integrative approach was adopted to consolidate knowledge distributed across information systems, strategic management, entrepreneurship, innovation management, and digital transformation research. Unlike a statistical meta-analysis, which estimates pooled relationships among comparable empirical variables, the present review focused on conceptual differentiation, organizational mechanisms, contextual influences, and the integration of findings derived from heterogeneous research designs. The analytical corpus comprised 32 scholarly publications dated between 2007 and 2026, including empirical investigations, theoretical contributions, and literature reviews. Of these publications, 24 were published between 2020 and 2026, providing a substantial representation of recent research while retaining foundational contributions necessary to explain the theoretical development of dynamic capabilities, AI-related organizational resources, and business model innovation.

Literature identification was organized around combinations of search terms covering the principal constructs and their organizational relationships. The terms included “artificial intelligence capability,” “AI capability,” “business model innovation,” “dynamic capabilities,” “SMEs,” “digital transformation,” “organizational adaptability,” “data-driven culture,” and “competitive advantage.”

These expressions provided the conceptual basis for locating publications addressing AI-related resources, organizational transformation, business model reconfiguration, and firm-level strategic outcomes. The selection emphasized peer-reviewed journal articles with direct conceptual or empirical relevance to at least one of the principal relationships examined in the review. Foundational theoretical publications were retained where their contributions were necessary to define organizational capabilities, explain resource reconfiguration, or establish the dimensions of business model innovation. Studies concentrating exclusively on the technical performance of AI algorithms, without substantive connections to organizational capabilities or business outcomes, fell outside the analytical scope. The resulting corpus was purposively structured to support theoretical integration across related research streams rather than to represent an exhaustive enumeration of all publications concerning AI adoption. Its coverage was consequently defined by conceptual relevance and the contribution of individual studies to the research questions.

The analytical procedure applied a theory-guided thematic synthesis organized around four principal dimensions: resource and capability foundations, organizational conversion mechanisms, contextual or boundary conditions, and strategic outcomes. The initial analytical classification drew on distinctions between organizational resources, capabilities, business model configurations, and competitive performance. AI-related technological infrastructure, data resources, and human expertise were classified as resource foundations, while AI capability was defined as the organizational capacity to coordinate and utilize these resources for analytical and operational purposes. Complementary organizational capabilities, including leadership, organizational adaptability, learning, and resource reconfiguration, were distinguished from AI capability itself. Governance arrangements, data-driven culture, organizational routines, and external knowledge integration were examined according to their supporting roles in converting AI-generated information into organizational activities. This classification established explicit conceptual boundaries and reduced the conflation of technological resources, complementary capabilities, organizational processes, and performance outcomes.

Thematic analysis proceeded through the identification of relevant constructs, the classification of reported relationships, and comparisons across the selected publications. Evidence was examined in relation to the theoretical propositions, empirical findings, and methodological orientations of individual studies. Within the four analytical dimensions, recurring mechanisms and contextual qualifications were identified and organized into more specific themes. The examination of organizational conversion mechanisms focused on sensing, opportunity recognition, organizational learning, experimentation, managerial coordination, and resource reconfiguration. Particular attention was given to business model innovation as a potential intermediary mechanism involving changes in value proposition, value creation and delivery, and value capture. Cross-study comparisons distinguished empirical associations reported by the original researchers from conceptual interpretations developed through the present synthesis. Differences in construct definitions, organizational settings, and research designs were considered when interpreting the consistency and applicability of relationships across studies.

The analysis of contextual conditions examined environmental dynamism, organizational maturity, sustainability orientation, innovation resilience, and external integration as factors potentially influencing the relationship between AI capability and strategic outcomes. These factors were not treated as interchangeable dimensions of AI capability, because their conceptual roles differed across the reviewed literature. Environmental dynamism and organizational circumstances were interpreted as contextual influences, while adaptability and external knowledge integration were examined according to their potential contributions to organizational adjustment and capability utilization. Strategic outcomes were classified according to reported associations with competitive advantage, innovation performance, operational effectiveness, organizational resilience, and sustainable firm performance. This differentiated treatment enabled the synthesis to identify common explanatory patterns without assuming that all studies employed equivalent constructs or demonstrated identical relationships.

The final stage integrated the identified themes into a capability-to-business-model pathway linking AI resource foundations, organizational utilization of AI capability, complementary conversion mechanisms, business model innovation, and context-dependent strategic outcomes. The pathway was developed by comparing the conceptual relationships and empirical associations identified across the four analytical dimensions and organizing them into a coherent explanatory sequence. The resulting framework distinguishes relationships supported by the reviewed literature from broader conceptual

propositions concerning the sequence and interaction of organizational processes. The synthesis is presented through comparative thematic explanations and analytical matrices rather than pooled effect sizes or newly estimated causal relationships. Methodological heterogeneity, differences in organizational settings, and variation in the operational definitions of AI capability and business model innovation were considered when interpreting the findings. The review consequently provides a structured conceptual synthesis of the selected literature, with conclusions confined to the explanatory relationships and evidence represented within its 32-source corpus.

RESULT AND DISCUSSION

AI Resource Foundations and Organizational Conversion in SMEs

The synthesis of the reviewed literature indicates that AI capability in SMEs cannot be reduced to the ownership or deployment of artificial intelligence applications because its strategic value depends on the configuration of multiple organizational resources. Technical infrastructure, data quality, managerial knowledge, employee expertise, governance mechanisms, and organizational routines collectively determine whether AI can be incorporated into business processes and strategic decision-making. Mikalef and Gupta (2021) conceptualize AI capability as a multidimensional organizational capability, while Enholm et al. (2022) similarly demonstrate that the business value of AI emerges from interactions between technological resources and complementary organizational conditions. This evidence suggests that SMEs should evaluate AI readiness through a capability portfolio rather than through the number or sophistication of AI tools acquired.

Technology and data constitute the initial resource layer because AI-based decision systems depend heavily on the availability, accessibility, and reliability of organizational information. Digital infrastructure enables firms to collect, process, and analyze increasingly complex data, but data resources generate strategic value only when they can be integrated into operational and managerial processes. Wamba-Taguimdje et al. (2020) demonstrate that AI-based transformation projects influence firm performance through the broader reconfiguration of organizational processes, while Borges et al. (2021) emphasize the strategic importance of integrating AI applications with existing organizational resources. For SMEs, the implication is that investment in AI should be accompanied by the development of consistent data-management routines and interoperable information systems.

Human expertise constitutes a second fundamental component because algorithmic outputs require interpretation, contextual judgment, and organizational translation. AI systems can improve prediction and information processing, yet employees and managers remain responsible for determining how analytical outputs should influence strategic and operational decisions. Chalmers et al. (2021) show that AI can expand entrepreneurial opportunity recognition, whereas Loureiro et al. (2021) emphasize that organizational capabilities and managerial understanding remain crucial for the effective use of AI in business. This relationship demonstrates that AI competence within SMEs requires the combination of technical literacy, domain-specific knowledge, experimentation skills, and the ability to critically evaluate machine-generated recommendations.

Organizational routines represent another critical resource because firms require repeatable processes that translate technological possibilities into consistent managerial action. Dynamic capabilities theory explains that competitive value emerges when organizations are able to sense environmental changes, seize emerging opportunities, and reconfigure resources accordingly (Teece, 2007). Warner and Wäger (2019) further demonstrate that digital transformation is an ongoing process of strategic renewal in which dynamic capabilities are gradually constructed through organizational learning and resource orchestration. In SMEs, this means that AI capability becomes strategically meaningful only when AI-supported information is embedded in routines for opportunity recognition, experimentation, coordination, and resource allocation.

Governance and managerial coordination provide the institutional mechanisms needed to align technical resources with organizational priorities. AI use can produce uncertainty concerning decision authority, accountability, employee roles, and the appropriate balance between automated and human judgment, making governance an integral element of capability development. Raisch and Krakowski (2021) describe this condition through the automation–augmentation paradox, which shows that organizational value depends on the way firms simultaneously manage technological substitution and human complementarity. Effective SME governance should therefore clarify responsibility for data quality, AI-supported decisions, performance monitoring, and the boundaries of managerial discretion.

Table 1. Resource Foundations of AI Capability and Their Organizational Functions in SMEs

Resource foundation	Organizational function	Strategic contribution	Representative evidence
AI and digital infrastructure	Provides computational and analytical capacity	Enables prediction, automation, and information processing	Wamba-Taguimdje et al. (2020); Borges et al. (2021)
Data resources	Supplies input for AI-supported analysis and learning	Improves evidence-based decisions and opportunity identification	Enholtm et al. (2022); Fosso Wamba et al. (2024)
Human expertise	Interprets and contextualizes AI-generated outputs	Supports augmentation, experimentation, and innovation	Chalmers et al. (2021); Loureiro et al. (2021)
Organizational routines	Embeds AI into repeated managerial and operational processes	Strengthens sensing, seizing, and reconfiguration	Teece (2007); Warner & Wäger (2019)
Governance and leadership	Defines accountability, coordination, and decision rights	Aligns AI use with organizational objectives	Raisch & Krakowski (2021); Ghosh (2024)
Data-driven culture	Normalizes evidence use across organizational functions	Converts analytical capacity into performance outcomes	Fosso Wamba et al. (2024)

The synthesis presented in Table 1 confirms that technological resources form only one part of the AI capability architecture and that strategic outcomes depend on the complementarity among multiple organizational assets. These resource categories interact rather than operate independently because data require infrastructure, analytical outputs require human interpretation, and technological recommendations require organizational routines and governance before they can influence business decisions. This interpretation is consistent with Verhoef et al. (2021), who conceptualize digital transformation as a multidimensional organizational phenomenon involving changes in resources, structures, processes, and value creation. The evidence therefore challenges technology-centric approaches that equate AI investment directly with organizational capability.

Data-driven culture plays a particularly important role in converting AI resources into organizational behavior because technological capacity alone does not guarantee that analytical evidence will influence decision-making. Fosso Wamba et al. (2024) demonstrate that data-driven culture mediates the relationship between AI capability and firm performance, indicating that employees and managers must routinely use data as a basis for decisions and experimentation. Mikalef and Gupta (2021) similarly associate AI capability with organizational creativity and performance, reinforcing the argument that the value of AI emerges through organizational practices rather than through technical assets in isolation. SMEs that institutionalize data-informed decision processes are therefore better positioned to transform limited AI investments into broader strategic capabilities.

Leadership and organizational adaptability further determine whether AI capabilities can be mobilized when market or technological conditions change. Ghosh (2024) identifies leadership and adaptability as central elements in developing AI capabilities for data-driven business model innovation, suggesting that managers must coordinate technological initiatives with broader organizational renewal. Digital transformation also requires leaders to manage uncertainty, establish priorities, and create space for experimentation because emerging technologies rarely produce predetermined organizational outcomes (Vial, 2019; Kitsios & Kamariotou, 2021). Adaptive leadership is particularly important for SMEs because concentrated decision structures can accelerate transformation when leaders actively support learning, but they can also constrain AI development when technology initiatives remain disconnected from strategic priorities.

The reviewed evidence additionally shows that external knowledge integration can strengthen internal AI capability by expanding the range and quality of information available to SMEs. Customer interactions, supplier relationships, digital platforms, consultants, and technology partners can provide

data, expertise, and complementary resources that smaller firms cannot efficiently develop internally. Dwivedi et al. (2021) highlight the broad organizational, policy, and managerial challenges surrounding AI adoption, while Mariani et al. (2023) emphasize the importance of integrating AI with innovation processes and organizational knowledge. External integration therefore functions as an extension of internal capability by allowing SMEs to combine their domain knowledge with resources obtained from actors in the wider business ecosystem.

A central finding from this subsection is that AI capability develops through organizational conversion rather than through technological accumulation. Technical infrastructure and data provide the capacity to generate intelligence, while human expertise, routines, governance, leadership, and culture determine whether that intelligence is translated into organizational action. The logic corresponds with Teece's (2018) argument that dynamic capabilities enable organizations to transform resources through sensing, seizing, and reconfiguration, and it is also consistent with the strategic AI literature emphasizing complementary organizational assets (Keding, 2021). AI investment should therefore be treated as the beginning of a capability-building process rather than as the final indicator of digital maturity.

Taken together, the findings suggest a sequential but interconnected process in which SMEs first establish technological and data foundations, subsequently develop human and managerial capabilities, and finally institutionalize organizational routines that allow AI-generated insights to influence strategic behavior. This pattern helps explain why similar technological investments can produce substantially different outcomes across firms because the strength of organizational complements determines the capacity to exploit AI resources. Haefner et al. (2021) show that AI increasingly affects innovation management by reshaping the processes through which organizations generate and evaluate new opportunities, while Wamba-Taguimdje et al. (2020) demonstrate that AI-related business value depends on organizational transformation. The strategic implication is that sustainable AI capability in SMEs should be understood as a coordinated system of technological, human, cultural, and managerial resources that prepares the organization for subsequent business model innovation.

Business Model Innovation as the Strategic Conversion Mechanism

The synthesis indicates that business model innovation represents the principal mechanism through which AI capability is converted into strategic and competitive outcomes. AI resources can expand organizational information-processing capacity, but such capacity only produces market value when it changes how firms create, deliver, and capture value. Business models therefore function as an organizational interface connecting internal technological capability with external customer and market outcomes (Zott et al., 2011; Foss & Saebi, 2017). This perspective is especially relevant for SMEs because resource limitations make it necessary to translate technological investments into identifiable improvements in value propositions, operational configurations, and revenue generation.

Business model innovation involves more than incremental process improvement because it requires meaningful modifications to the architecture of organizational value creation. Clauss (2017) conceptualizes business model innovation through changes in value proposition, value creation and delivery, and value capture, providing a multidimensional framework for examining how digital technologies reshape organizational activity. AI can influence each of these dimensions by enabling personalized products, automated interactions, predictive services, real-time decision-making, and new forms of data-based monetization. Consequently, the strategic importance of AI depends on whether these technological possibilities become embedded in the structure of the firm's business model.

The value-proposition dimension represents one of the most visible manifestations of AI-enabled business model innovation. AI-supported analytics can identify emerging customer needs, detect consumption patterns, segment markets more precisely, and support the development of differentiated products and services. Haefner et al. (2021) argue that AI can reshape innovation management by improving opportunity identification and knowledge recombination, while Chalmers et al. (2021) emphasize its capacity to support entrepreneurial opportunity creation. SMEs can therefore use AI not merely to automate existing offerings but also to discover new combinations of customer problems, solutions, and market opportunities.

AI capability also changes the architecture through which value is created and delivered by reorganizing operational processes, coordination mechanisms, and decision structures. Automation can reduce repetitive activities, predictive analytics can improve resource allocation, and intelligent

information systems can support faster responses to market changes. Sharma and Dang (2026) identify a transformative role for AI in improving business-process performance, while Wamba-Taguimdje et al. (2020) show that AI-related value emerges through broader transformation projects rather than isolated technological implementation. These findings indicate that AI-enabled business model innovation requires SMEs to redesign internal processes simultaneously with technological adoption.

The value-capture dimension provides another important pathway through which AI can influence firm competitiveness because digital intelligence can support new pricing structures, revenue models, customer-retention mechanisms, and platform-based transactions. Business model research emphasizes that firms achieve strategic benefits when innovations in value creation are matched by mechanisms that allow them to appropriate part of the resulting economic value (Teece, 2018; Foss & Saebi, 2017). AI can strengthen value capture by improving demand forecasting, customer lifetime-value estimation, dynamic pricing, and the identification of profitable market segments. SMEs therefore need to evaluate AI initiatives not only according to efficiency improvements but also according to their ability to generate sustainable economic returns.

Table 2. AI-Enabled Business Model Innovation Pathways in SMEs

Business model dimension	AI-enabled mechanism	Organizational change	Expected strategic outcome	Representative evidence
Value proposition	Customer analytics, personalization, opportunity recognition	Development of differentiated products and services	Customer relevance and differentiation	Haefner et al. (2021); Chalmers et al. (2021)
Value creation	Automation, predictive analytics, process intelligence	Redesign of activities and workflows	Efficiency and responsiveness	Wamba-Taguimdje et al. (2020); Sharma & Dang (2026)
Value delivery	Intelligent channels and digital interaction	Reconfiguration of customer interfaces	Faster and more adaptive service delivery	Verhoef et al. (2021); Ghosh (2024)
Value capture	Data-supported pricing and revenue optimization	New monetization and revenue mechanisms	Improved economic appropriation	Teece (2018); Foss & Saebi (2017)
Strategic renewal	AI-supported experimentation and learning	Continuous adaptation of the business model	Competitive advantage and resilience	Shao et al. (2026); Zhang et al. (2024)

The synthesis summarized in Table 2 demonstrates that AI can simultaneously affect multiple components of the business model, although the strength and sequence of these effects may differ across organizational contexts. Business model transformation is therefore unlikely to follow a single standardized pathway because SMEs differ in resources, sectoral conditions, technological maturity, and access to data. Ghosh (2024) shows that organizational adaptability and leadership shape the development of AI capabilities for data-driven business model innovation, suggesting that managerial capacity influences which business model components are transformed first. The conversion of AI capability into business model innovation should thus be understood as a context-dependent process rather than an automatic technological consequence.

Recent empirical evidence provides particularly strong support for the mediating role of business model innovation. Shao et al. (2026) report that business model innovation mediates the relationship between AI capability and enterprise competitive advantage, directly reinforcing the argument that technological resources require an organizational conversion mechanism before they generate strategic outcomes. This mediation logic also helps explain why firms possessing similar AI technologies may experience substantially different performance results. Competitive advantage emerges when firms are capable of embedding AI-generated knowledge into the design of value propositions, internal activity systems, customer relationships, and revenue structures.

The strategic effect of business model innovation is also associated with organizational learning and innovation resilience. Zhang et al. (2024) demonstrate that digital intelligence transformation can influence innovation resilience and firm performance, indicating that the ability to adapt business architectures may help organizations remain effective under uncertain conditions. Brabete et al. (2026) similarly characterize AI as evolving from a source of operational efficiency toward a broader strategic meta-capability linked with firm performance. These findings suggest that business model innovation should not be treated as a one-time redesign but as an ongoing capability for reconfiguring value creation when technological and competitive environments change.

Digital innovation also strengthens the relationship between technological capability and business model transformation by enabling firms to combine different digital resources into new organizational configurations. Alqahtani et al. (2024) associate AI, cloud computing, digital capabilities, digital innovation, and IT flexibility with firm performance, illustrating that AI rarely operates independently from other digital resources. Ciampi et al. (2022) further show that digital technologies and sustainable business models can co-evolve in ways that affect firm performance. These findings highlight the importance of complementarity, because SMEs can achieve greater strategic value when AI capability is integrated with flexible digital infrastructure, organizational learning, and continuous experimentation.

The results further indicate that business model innovation allows SMEs to combine efficiency-oriented and novelty-oriented strategies rather than choosing only one of them. AI-based automation and process analytics can support cost reduction and operational reliability, whereas personalization, digital services, and rapid experimentation can enhance differentiation and innovation. Singh et al. (2026) associate AI with business innovation and entrepreneurship, reinforcing the view that artificial intelligence can simultaneously strengthen exploitation of existing operations and exploration of new opportunities. The ability to balance these two logics may be particularly important for SMEs seeking competitive advantage without possessing the resource scale available to larger firms.

Overall, the evidence supports a capability-to-business-model pathway in which AI resources first strengthen sensing, prediction, learning, and experimentation and subsequently enable changes in value proposition, value architecture, and value capture. This pathway clarifies why business model innovation functions as a strategic conversion mechanism rather than merely as another organizational outcome. Shao et al. (2026), Ghosh (2024), and Brabete et al. (2026) collectively indicate that AI produces greater strategic value when technological capability is transformed into broader organizational and business-model renewal. SMEs should therefore assess the maturity of AI capability by examining the extent to which it enables continuous redesign of value creation and appropriation rather than by measuring technological adoption alone.

Boundary Conditions, Sustainability, and Strategic Implications for SMEs

The synthesis demonstrates that the strategic value of AI capability is contingent on the organizational and environmental conditions under which it is deployed. Firms do not operate in homogeneous environments, and differences in market turbulence, technological change, competitive intensity, regulation, resource availability, and organizational maturity can strengthen or weaken the contribution of AI to business outcomes. Dynamic capability theory provides a useful explanation because sensing, seizing, and reconfiguration become particularly important when organizations face rapidly changing external conditions (Teece, 2007, 2018). AI capability should therefore be interpreted as context dependent rather than as a universally effective resource that produces equivalent performance outcomes across all SMEs.

Environmental dynamism emerges as one of the most important boundary conditions because rapidly changing markets increase the value of timely information, prediction, experimentation, and organizational adaptation. Shahid et al. (2026) show that environmental dynamism moderates the relationship surrounding AI capabilities, innovative work behavior, and sustainable firm performance, indicating that external volatility influences the strategic usefulness of AI-enabled capabilities. Ghosh (2024) similarly highlights organizational adaptability as a critical element in the development of AI capabilities for data-driven business model innovation. SMEs operating in dynamic environments may therefore derive greater benefit from AI when they possess sufficient organizational flexibility to translate new information into rapid strategic responses.

Innovation resilience constitutes another important mechanism because organizations increasingly need to sustain innovative activity despite technological disruption, competitive uncertainty, and resource limitations. Zhang et al. (2024) connect enterprise digital intelligence transformation with innovation resilience and firm performance, suggesting that digital capability contributes not only to immediate efficiency but also to the capacity to respond to disruption. Brabete et al. (2026) similarly describe the evolving relationship between AI and firm performance as moving from operational efficiency toward a broader strategic meta-capability. These findings indicate that AI capability becomes more strategically significant when it strengthens the ability of SMEs to learn, adapt, and reorganize their innovation activities under changing conditions.

Sustainability further expands the strategic role of AI by connecting technological transformation with environmental and stakeholder-oriented outcomes. Farmanesh et al. (2025) associate artificial intelligence and green innovation in SMEs with competitive advantage and progress toward sustainable development goals, demonstrating that AI can support objectives beyond short-term financial performance. Ciampi et al. (2022) likewise identify a co-evolutionary relationship between digital technologies and sustainable business models that can influence firm performance. These studies imply that AI-enabled business model innovation becomes more strategically valuable when environmental considerations are incorporated into value creation, operational processes, and long-term competitive positioning.

The relationship between AI capability and sustainability nevertheless depends on organizational complements because digital technologies cannot independently produce environmentally responsible outcomes. Firms require knowledge integration, employee participation, innovation-oriented routines, managerial commitment, and performance-monitoring systems capable of translating analytical information into sustainable operational decisions. Shahid et al. (2026) emphasize innovative work behavior as an important mechanism in the AI capability–sustainable performance relationship, while Farmanesh et al. (2025) connect AI, green innovation, and competitive advantage within SMEs. Sustainability should therefore be treated as an organizational transformation objective that requires the coordinated development of technological and behavioral capabilities.

Table 3. Boundary Conditions and Strategic Outcomes of AI Capability in SMEs

Boundary condition / complementary factor	Role in AI-enabled transformation	Expected organizational effect	Strategic implication for SMEs	Representative evidence
Environmental dynamism	Increases the value of sensing and rapid adaptation	Faster strategic response	Develop flexible decision and experimentation routines	Shahid et al. (2026); Teece (2007)
Organizational adaptability	Facilitates resource and business model reconfiguration	Improved responsiveness to technological and market change	Align AI initiatives with adaptive leadership	Ghosh (2024)
Innovation resilience	Supports continued innovation under disruption	Greater continuity of innovative activity	Use digital intelligence for learning and reconfiguration	Zhang et al. (2024)
Sustainability orientation	Directs AI toward environmental and stakeholder value	Green innovation and sustainable performance	Integrate sustainability into AI-enabled business models	Farmanesh et al. (2025); Ciampi et al. (2022)
Digital complementarity	Combines AI with other digital resources	Stronger transformation capability	Avoid isolated technology investments	Alqahtani et al. (2024); Verhoef et al. (2021)

Human managerial capability	and	Converts analytical into organizational action	Improved judgment, innovation, and coordination	Develop literacy and managerial governance	digital and	Mikalef & Gupta (2021); Dwivedi et al. (2021)
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Table 3 indicates that AI capability generates stronger strategic outcomes when complementary organizational and contextual factors support its conversion into adaptive behavior. Environmental dynamism can increase the usefulness of AI-supported sensing, while adaptability, resilience, and sustainability orientation determine how technological information is incorporated into strategic action. This interpretation is consistent with Verhoef et al. (2021), who emphasize the multidimensional nature of digital transformation, and Alqahtani et al. (2024), who demonstrate the interconnected roles of AI, cloud computing, digital capabilities, digital innovation, and IT flexibility. The evidence therefore supports a complementarity perspective in which AI should be developed as part of an integrated digital and organizational capability system.

Resource constraints make such complementarity particularly significant for SMEs because smaller firms cannot always reproduce the extensive technological infrastructures or specialist teams available to larger organizations. This limitation does not necessarily prevent effective AI adoption, but it increases the importance of prioritization, resource orchestration, partnerships, and staged capability development. The broader innovation-management literature recognizes that innovation requires coordinated management of technological opportunities and organizational processes rather than isolated invention or technology acquisition (Chen et al., 2019; Haefner et al., 2021). SMEs can therefore reduce transformation risk by directing scarce resources toward AI applications that address clearly defined strategic problems and can subsequently be expanded through organizational learning.

The findings also suggest that digital complementarity should guide the sequencing of AI investment. AI applications become more useful when they are supported by reliable data, flexible digital systems, managerial expertise, organizational learning, and mechanisms that connect technological insights with business decisions. Kitsios and Kamariotou (2021) emphasize the relationship between AI, business strategy, and digital transformation, while Keding (2021) shows that the interaction between AI and strategic management has increasingly become an organizational rather than purely technological issue. A staged strategy that first establishes foundational data and governance capabilities before expanding experimentation and business model redesign may therefore be more appropriate for resource-constrained SMEs than simultaneous large-scale technology deployment.

Human-centered implementation remains critical within this sequencing process because expanding automation can alter employee roles, knowledge requirements, and decision authority. Raisch and Krakowski (2021) demonstrate that organizations must address the automation–augmentation paradox, while Dwivedi et al. (2021) identify organizational and managerial challenges associated with the increasing use of AI. Loureiro et al. (2021) likewise emphasize the need for future business research to examine the organizational consequences of AI alongside its technological potential. SMEs should consequently develop employee skills and managerial governance in parallel with technological investments so that AI strengthens rather than fragments organizational decision-making.

The results further reveal that external integration can compensate for internal resource limitations and broaden the innovation capacity of SMEs. Collaboration with technology providers, customers, suppliers, universities, consultants, and digital-platform partners can provide access to knowledge, data, technological infrastructure, and specialized skills that are difficult to develop internally. Mariani et al. (2023) position AI within a broader innovation ecosystem involving multiple streams of knowledge and organizational interaction, while Singh et al. (2026) associate AI with business innovation and entrepreneurial development. External integration should therefore be viewed as part of AI capability architecture rather than simply as a procurement relationship with technology vendors.

Sustainable competitive advantage ultimately depends on the ability of firms to continually recombine technological and organizational resources rather than on any single AI implementation. Mikalef and Gupta (2021) demonstrate that AI capability is associated with creativity and firm performance, whereas Fosso Wamba et al. (2024) show that data-driven culture provides an important

organizational mechanism through which AI capability is translated into performance. The combination of these findings with research on environmental dynamism, resilience, and sustainability indicates that the strongest strategic effects occur when technological resources are embedded within learning-oriented and adaptive organizational systems. AI capability thus represents an evolving configuration of resources whose value depends on continuous organizational renewal.

Taken together, the three analytical dimensions developed in this review reveal an integrated pathway from AI resource foundations to organizational conversion, business model innovation, and context-dependent strategic outcomes. AI infrastructure, data, human expertise, governance, and organizational routines establish the capability base; sensing, learning, experimentation, and adaptability convert that base into changes in value creation; and environmental dynamism, resilience, sustainability orientation, and external integration shape the resulting performance effects. This interpretation is consistent with research viewing digital transformation as strategic renewal (Warner & Wäger, 2019; Vial, 2019) and with evidence that AI-based transformation produces value through organizational rather than technological change alone (Wamba-Taguimdje et al., 2020; Enholm et al., 2022). For SMEs, the central implication is that sustainable competitive advantage depends less on acquiring increasingly sophisticated AI tools than on constructing a coherent capability system capable of continuously transforming AI resources into adaptive, innovative, and sustainable business models.

CONCLUSION

This integrative review identifies business model innovation as a central conceptual mechanism linking AI capability with competitive outcomes in small and medium-sized enterprises. The synthesis distinguishes AI-related technological, informational, and human resources from the organizational capability required to utilize them and from complementary processes that support strategic transformation. The principal theoretical contribution is a capability-to-business-model pathway that connects AI resource foundations, organizational conversion mechanisms, changes in value proposition, value creation and delivery, and value capture, and context-dependent strategic outcomes. This framework clarifies the distinct roles of AI capability, organizational adaptability, managerial coordination, and business model innovation while integrating previously differentiated explanations from information systems, strategic management, entrepreneurship, and innovation research. The reviewed evidence supports the relevance of these relationships but does not establish a universal or deterministic progression from AI investment to competitive advantage.

The findings have practical implications for the development of AI capabilities under the resource constraints commonly experienced by SMEs. Managerial priorities include improving data reliability, establishing proportionate governance arrangements, developing employee and managerial competencies, and integrating AI-supported information into organizational decision-making. Experimentation with customer offerings, operational processes, service delivery, and revenue arrangements provides potential opportunities for translating technological capabilities into business model changes. The appropriate sequence and scale of these activities depend on firm size, technological maturity, available resources, industry characteristics, and external institutional conditions. External partnerships and organizational learning may complement internal capability development, particularly where specialist expertise and technological infrastructure are limited. These implications support context-sensitive capability development rather than a uniform implementation model.

The interpretation of the findings is subject to limitations associated with the purposive selection of 32 scholarly sources, differences in research designs and construct definitions, and potential publication and source-coverage biases. The integrative synthesis does not provide exhaustive evidence coverage, pooled effect estimates, or independent empirical verification of the proposed relationships. The direction, magnitude, and causal structure of the capability-to-business-model pathway consequently remain open to empirical examination. Future research can assess the proposed distinctions through longitudinal and comparative studies across industries, institutional environments, and SME maturity levels. Particular attention is warranted to the mediating role of business model innovation and the potentially moderating effects of environmental dynamism, data accessibility, regulatory conditions, organizational adaptability, and sustainability orientation. Such investigations would establish the circumstances under which AI capability and complementary organizational processes are associated with durable business model innovation and competitive performance.

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