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ARTIFICIAL INTELLIGENCE ADOPTION AND FIRM PERFORMANCE IN SMES A SYSTEMATIC LITERATURE REVIEW AND FUTURE RESEARCH AGENDA

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Abstract

The relationship between artificial intelligence (AI) adoption and firm performance in small and medium-sized enterprises (SMEs) has attracted growing scholarly attention, yet the literature remains theoretically fragmented and dominated by techno-optimistic assumptions that portray AI as a direct pathway to superior performance. This study addresses two central research questions: why do AI adoption outcomes remain heterogeneous across SMEs, and through what organizational mechanisms does AI create business value? A systematic search of the Scopus database, followed by PRISMA-guided screening, yielded 29 peer-reviewed articles analyzed through VOS viewer bibliometric mapping and qualitative content analysis. Four thematic clusters were identified: AI Adoption and SME Sustainable Performance; AI Investment and Firm-Level Heterogeneity; Green Intellectual Capital and Innovation; and AI Application and Service Productivity in China. Drawing on these clusters, an integrative Antecedents-Mediators-Moderators-Outcomes (AMMO) framework is proposed. Findings demonstrate that AI adoption outcomes are contingent upon complementary organizational capabilities, knowledge management infrastructure, human capital quality, and institutional context rather than technology deployment alone. Five value-creating mechanism categories are identified: innovation and transformation, human capital and knowledge, operational and productivity, strategic and behavioral, and financial and investment mechanisms. The study contributes by challenging techno-deterministic assumptions, advancing the AMMO framework as a conceptual architecture for future inquiry, and positioning green intellectual capital as an emerging theoretical frontier. Implications for managers, policymakers, and future researchers are discussed.

Keywords: artificial intelligence adoption; firm performance; SMEs; systematic literature review; AMMO framework

INTRODUCTION

The rapid advancement of artificial intelligence (AI) has fundamentally transformed the contemporary business landscape, positioning AI as a strategic enabler for Micro, Small, and Medium Enterprises (MSMEs). The emergence of generative AI, large language models, and AI-enabled business systems has accelerated the diffusion of intelligent technologies beyond large corporations toward resource-constrained firms. Recent studies indicate that AI enables MSMEs to improve real-time decision-making, strengthen operational efficiency, develop innovative business models, and enhance customer engagement through predictive analytics and personalization capabilities (Carayannis et al., 2024; Gabelaia & Hendieh, 2025; Musa et al., 2025). In this context,

Vol. 02 Year 2026, Hal 1886 – 1906
ISSN: 3309 - 3337

AI is no longer merely a technical tool but increasingly conceptualized as a strategic capability supporting digital transformation and organizational competitiveness in dynamic markets.

Existing literature has coalesced around several dominant paradigms. AI is predominantly framed as a catalyst of digital transformation capable of modernizing MSME operations (Koundal & Koundal, 2026; Wolor et al., 2025), frequently analyzed through the Technology–Organization–Environment framework and Dynamic Capability Theory (Abaddi, 2025; Muhammad et al., 2025), and linked to sustainability and ESG-oriented outcomes (Kulkarni et al., 2023). AI applications including chatbots, inventory automation, forecasting systems, and intelligent analytics are argued to reduce operational costs, optimize resource allocation, and accelerate innovation while improving customer satisfaction and market reach (Aljabari et al., 2024; Bhalla, 2025; Cagiza et al., 2025; Marcineková et al., 2025; Mehra et al., 2025; Melnyk, 2025; Pérez-Uribe et al., 2026; Thakur et al., 2025). Collectively, these perspectives reinforce a techno-optimistic assumption that AI adoption naturally translates into superior organizational performance.

However, empirical findings regarding AI-enabled performance outcomes remain fragmented and inconsistent. Research on human-AI collaboration demonstrates that opaque AI systems and algorithmic biases may reduce decision quality and weaken organizational trust (Deng et al., 2025), while real-world implementation studies reveal that AI systems frequently experience substantial declines in effectiveness due to interoperability problems, poor data quality, and implementation mismatch (El Arab et al., 2025; Kumar et al., 2025). These inconsistencies are particularly acute in MSMEs, which face severe resource constraints, limited technological expertise, inadequate data infrastructure, and high implementation risk (Waidringer et al., 2026). Unlike large firms with structured governance mechanisms, MSMEs tend to adopt AI incrementally in response to immediate operational challenges and concentrate utilization in narrower domains such as marketing automation and customer service (Pérez-Campdesuñer et al., 2025; Rangappan & Ueasangkomsate, 2026). Moreover, prior studies predominantly focus on adoption intention or direct performance relationships while offering only partial explanations of how AI actually influences innovation capability, knowledge integration, or strategic decision-making (Sánchez-Rodríguez et al., 2025; Taksi Deveciyan et al., 2026; Zhang & Peng, 2025), reflecting a broader tendency toward outcome-oriented and techno-deterministic perspectives that neglect process-oriented and organizationally embedded explanations.

Given these unresolved tensions, this study systematically reviews and critically synthesizes the literature on AI adoption and MSME performance by addressing two central research questions: (1) why do AI adoption outcomes remain heterogeneous across MSMEs, and (2) through what organizational mechanisms does AI create business value in MSMEs? By doing so, this study moves beyond dominant techno-optimistic assumptions toward a more nuanced, process-oriented, and theoretically integrated understanding of AI-enabled organizational transformation in MSMEs.

RESEARCH METHOD

This study follows the systematic literature review (SLR) protocol outlined by Anggadwita and Indarti (2023), encompassing four sequential stages: review planning, definition of inclusion and exclusion criteria, data retrieval and selection, and data analysis and synthesis. Both quantitative and qualitative methods are employed: the former maps article profiles through descriptive statistics, while the latter adopts comprehensive literature analysis.

2.1. Planning the review

The planning phase involves formulating research questions and establishing scientific search parameters (García-Peñalvo, 2022; Priyadarshi et al., 2021; Suchek et al., 2021). Three research objectives were identified: (1) to identify research profiles in the literature on AI adoption and firm performance in SMEs; (2) to examine thematic clusters characterizing the current body of knowledge; and (3) to identify emerging research opportunities.

2.2. Inclusion and exclusion criteria

Inclusion and exclusion criteria were established to ensure appropriate study selection and maintain review integrity (Indarti et al., 2021; Okoli, 2015; Paul et al., 2021; Suhartanti et al., 2025). Retained articles were written in English, published in peer-reviewed journals, and indexed in credible outlets not listed in Beall's List.

2.3. Data retrieval and selection

Articles were retrieved from the Scopus database, recognized for its academic rigor and comprehensiveness in social science research (Baas et al., 2020; Mongeon & Paul-Hus, 2016; Sitalaksmi et al., 2024). The search string combined SME and performance terminology adapted from Dvouletý et al. (2021) with AI-specific terms identified by the authors:

"micro firm" OR "micro business" OR "micro enterprise" OR "micro compan*" OR "small firm" OR "small business" OR "small enterprise" OR "small firm" OR "small compan*" OR SME OR "Small and medium-sized enterprise" OR "Medium-sized business" OR "Medium-sized firm" OR "Medium-sized enterprise" OR "Medium-sized firm" OR "Medium-sized compan*"

AND

"firm performance" OR productivity OR profit* OR employment OR revenue* OR turnover OR sales OR "value added" OR return* to capital OR investment OR assets OR "production capacity" OR "firm size"

AND

"artificial intelligence" OR AI OR "generative AI" OR GenAI OR ChatGPT OR "large language model*" OR LLM OR chatbot* OR "AI system*"

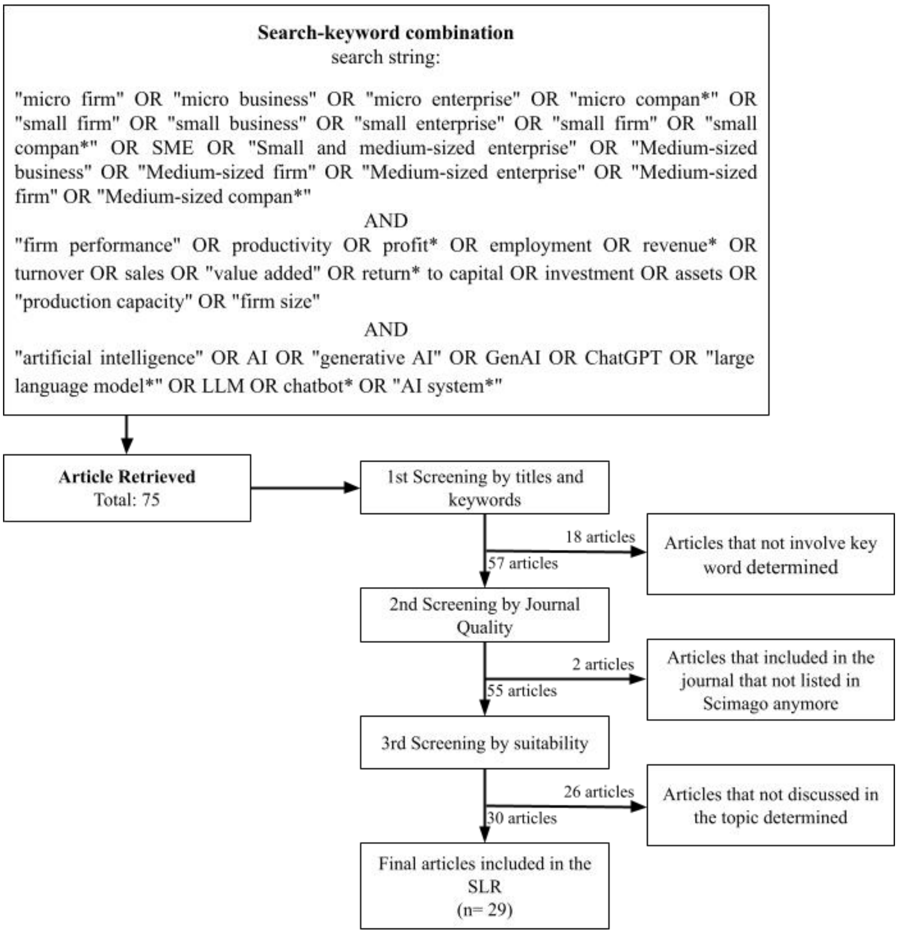

Figure 1 Data Selection Process (Author's own work)

Only peer-reviewed journal articles published in English were considered, as such sources yield greater academic influence (Podsakoff et al., 2005). The data range extended to 19 May 2026 without a lower-bound restriction, capturing the earliest emergence of the topic.

The PRISMA protocol was systematically applied across sequential filtering stages. Following language restriction, 75 articles were initially identified. Title and abstract screening reduced this to 57 papers. Exclusion of journals no longer indexed in Scimago Journal Ranking yielded 55 articles. A final content-relevance screening eliminated studies that did not examine AI adoption and organizational performance in SMEs, focused on technical algorithms, macro-level or engineering perspectives, adoption determinants rather than performance outcomes, non-SME contexts, or utilized AI solely as a methodological tool rather than as an adopted organizational technology. This produced a final dataset of 29 articles. The selection process is illustrated in Figure 1.

2.4. Data Analysis and Synthesis

Each article was profiled by documenting publication year, journal source, publisher, ranking, and unit of analysis, providing a baseline overview of temporal trends and leading publication outlets. A qualitative content analysis was subsequently conducted to capture research findings, methodological approaches, and thematic concerns, enabling identification of dominant themes and underexplored gaps (Sitalaksmi et al., 2024).

To complement content analysis, a bibliometric approach was applied using VOSviewer software, as recommended in systematic review practice (Fauzi et al., 2022; Sofiyanti & Adawiyah, 2023). Co-word analysis based on article titles and abstracts detected thematic clusters and research streams. A co-occurrence threshold of five retained only frequently recurring keywords, while the Donohue (1974) formula calculated keyword frequencies, yielding 67 high-frequency terms after excluding two unrelated keywords. The resulting network map provided a visual representation of keyword interconnections, enabling deeper exploration of the intellectual structure underlying the literature on AI adoption and MSME performance.

RESULTS AND DISCUSSION

3.1. Investigation of reviewed articles

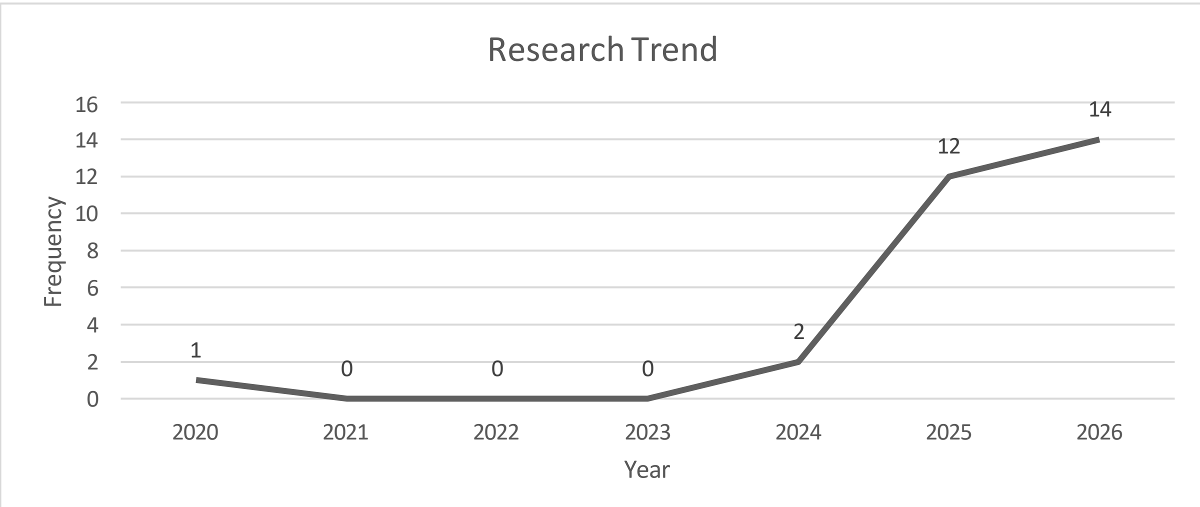

Figure 2 Research Trend

The initial Scopus search yielded 75 articles, of which 29 specifically addressed AI adoption and firm performance in SMEs. As shown in Figure 2, publication activity was minimal before 2024, with one article in 2020 and none in 2021–2023, reflecting the nascent nature of this intersection during that period. A sharp inflection occurred in 2024 with two publications, followed by 12 articles in 2025 and 14 in 2026. The concentration of nearly 90% of all publications within this two-year window indicates that the topic has reached a critical mass of scholarly attention, driven largely by

Vol. 02 Year 2026, Hal 1886 – 1906
ISSN: 3309 - 3337

the mainstreaming of generative AI technologies and their increasingly observable effects on SME performance. This recency simultaneously signals that the literature remains in a formative stage with significant theoretical and empirical gaps.

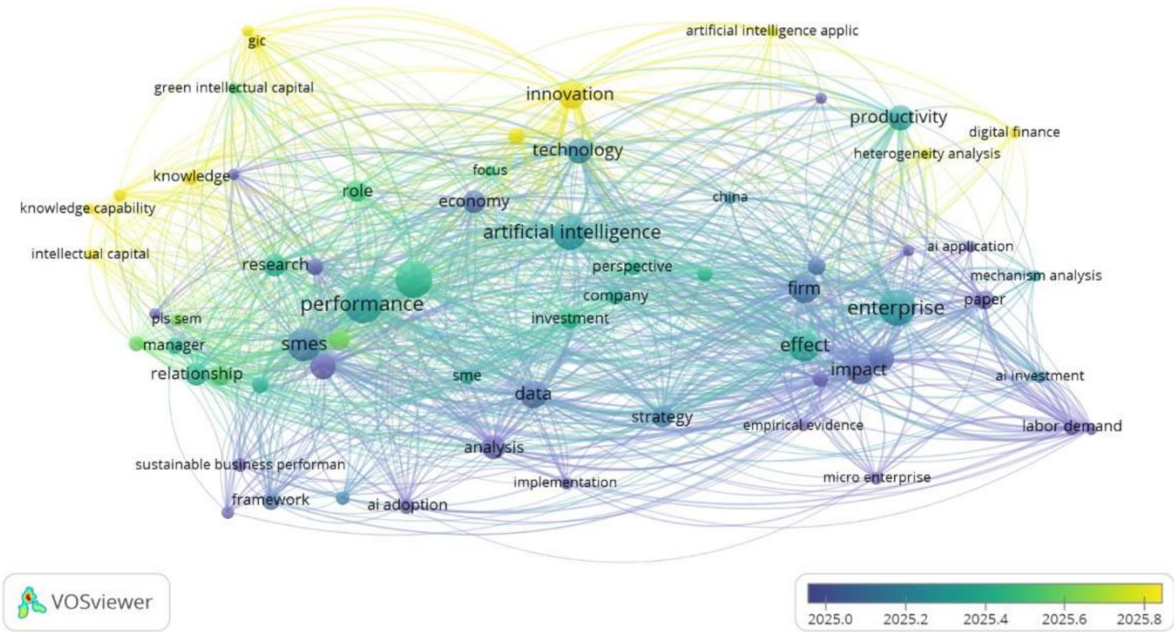

Figure 3 Overlay Visualisation

Overlay and density visualizations (Figures 3 and 4) trace the evolution and intensity of research keywords. In the overlay map, earlier contributions include impact, effect, ai investment, labor demand, empirical evidence, micro enterprise, ai adoption, and pls sem, suggesting that firm-level impact assessment, labour market consequences, and structural equation modelling constituted the foundational concerns of the emerging literature. Mid-period consolidation is reflected in transitional nodes such as artificial intelligence, performance, smes, data, strategy, technology, and productivity, indicating the establishment of dominant theoretical and empirical vocabulary. The most recently emerging keywords, including innovation, gic, knowledge capability, intellectual capital, heterogeneity analysis, and digital finance, signal a frontier in which scholars are extending discourse toward knowledge-based resources, green intellectual capital, and financing mechanisms as boundary conditions of AI-driven performance. The density visualization reveals two dominant hotspots: a left-centre zone anchored by performance, smes, relationship, manager, and pls sem, confirming performance outcomes as the gravitational core of the literature; and a right-side cluster centred on enterprise, effect, impact, and firm, representing firm-level consequences of AI deployment. Peripheral low-density keywords such as digital finance, heterogeneity analysis, gic, and intellectual capital underscore research gaps requiring systematic future attention.

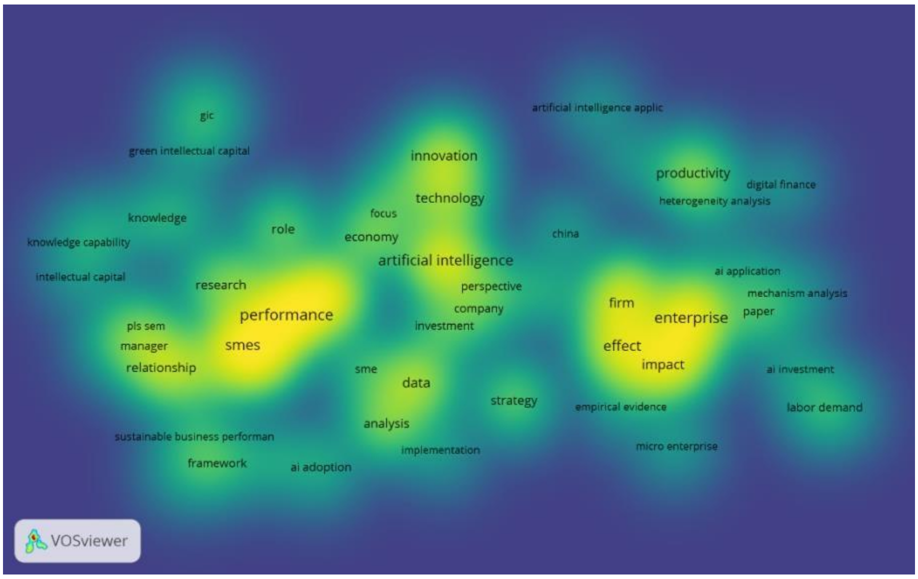

Figure 4 Density Visualisation

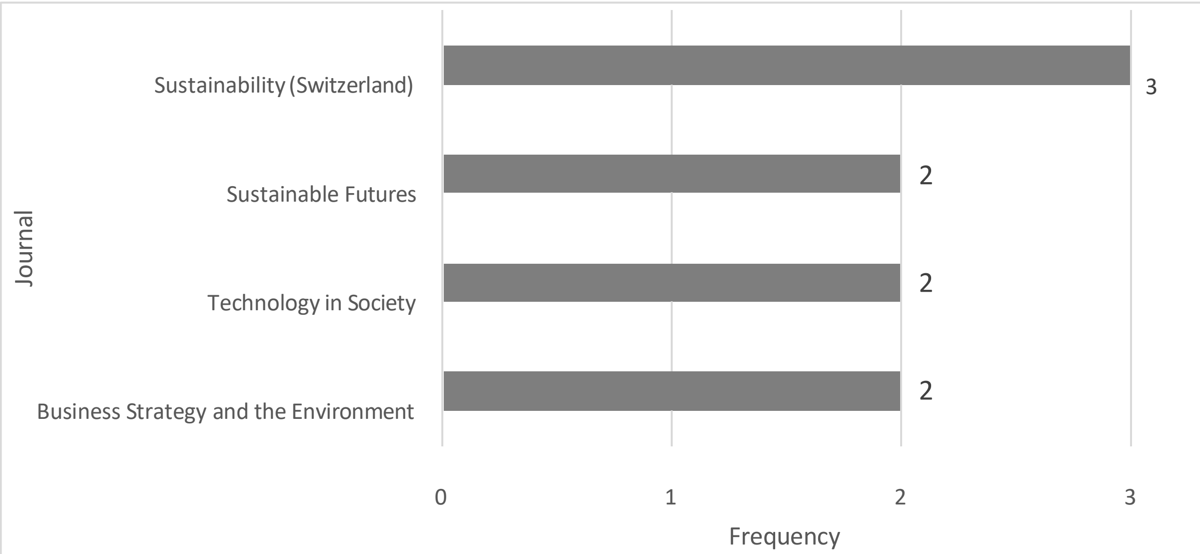

Figure 5 Top Journal List

Regarding publication outlets (Figure 5), Sustainability (Switzerland) is the most productive platform with three articles, followed by Business Strategy and the Environment, Technology in Society, and Sustainable Futures with two articles each. The remaining 21 articles appeared in distinct journals spanning management, economics, sustainability, information systems, and engineering, underscoring the cross-disciplinary and fragmented nature of the literature. The dominance of sustainability-oriented journals suggests that AI-SME performance research is increasingly framed within environmental and sustainable development perspectives. In terms of journal quality (Figure 6), 17 articles appeared in Q1 outlets and nine in Q2, collectively representing nearly 90% of all publications, with no contributions recorded in Q4 journals.

Vol. 02 Year 2026, Hal 1886 – 1906
ISSN: 3309 - 3337

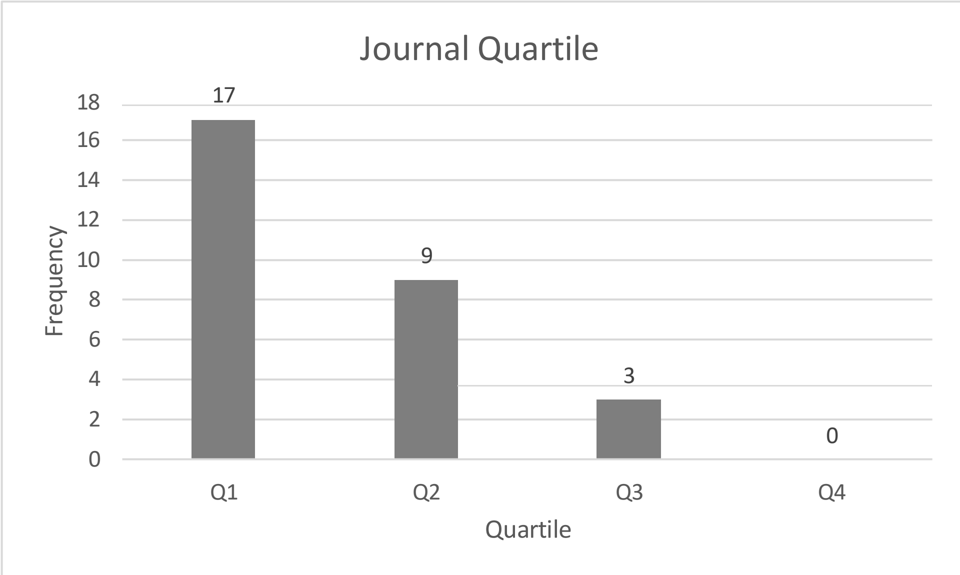

Figure 6 Journal Quality

3.2. Mapping The Current State of Research

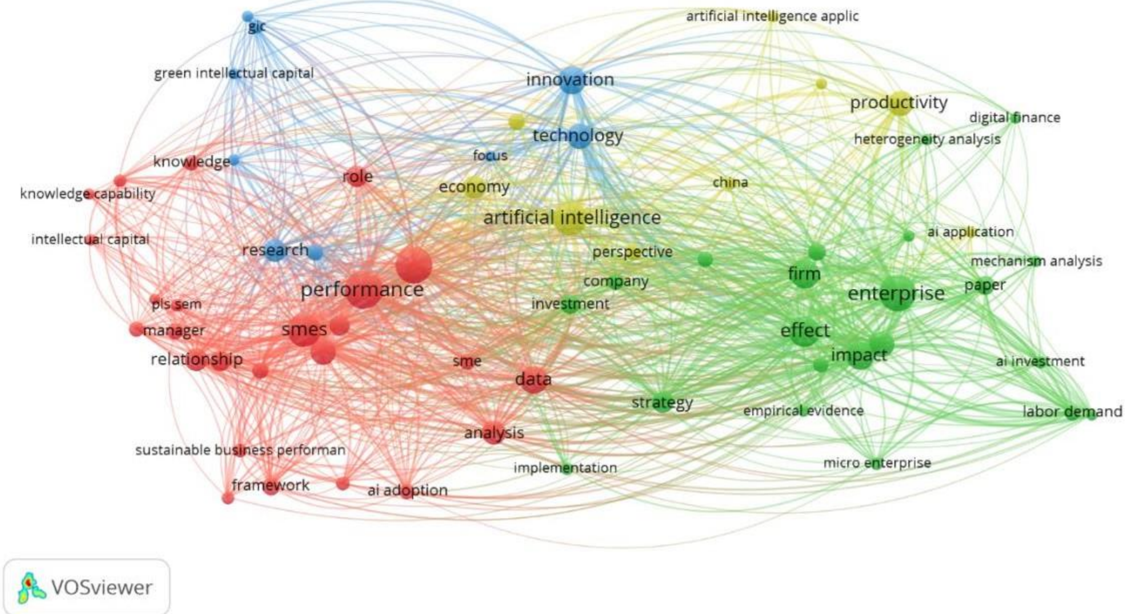

Figure 7 Network Visualisation

Cluster 1 *AI Adoption and SME Sustainable Performance.* This dominant stream examines the conditions, resources, and organizational factors shaping the AI adoption-performance relationship, predominantly through PLS-SEM approaches grounded in the Resource-Based View and Dynamic Capabilities Theory. AI adoption enhances SME performance through capability-mediated pathways: knowledge management, intellectual capital, and competitive advantage function as sequential mediating mechanisms generating sustainable organizational outcomes (Anjum et al., 2026). Badghish and Soomro (2024), applying the TOE framework among Saudi Arabian SMEs, identify relative advantage, compatibility, sustainable human capital, and government support as critical antecedents, with AI exerting significant influence on both

Vol. 02 Year 2026, Hal 1886 – 1906
ISSN: 3309 - 3337

operational and economic performance. Rahmani et al. (2026) demonstrate that AI usage intensity alone does not guarantee performance improvement, underscoring the indispensability of complementary dynamic capabilities, data governance, and human capital. Dinh (2026) further shows that AI-enabled knowledge capabilities operate through dual pathways, directly enhancing new product performance and indirectly through digital product innovation radicalness, with digital sustainability leadership as a critical boundary condition. Ratanacharoenchai and Jantapoon (2026) confirm that AI capabilities enhance supply chain resilience, which fully mediates the AI-social sustainability relationship. Collectively, these studies establish that AI-enabled performance outcomes are neither uniform nor automatic, but contingent upon strategic deployment choices, resource complementarity, and organizational absorptive capacity (Graham & Matikonis, 2025; Ha et al., 2025).

Table 1 Clustering Label

Cluster	Keywords	Label
Cluster 1 Red	adoption; ai adoption; analysis; competitive advantage; context; data; firm size; framework; intellectual capital; knowledge; knowledge capability; manager; moderating role; performance; pls sem; policymaker; process; relationship; resource; role; sme; smes; study; sustainability; sustainable business performance	AI Adoption & SME Sustainable Performance
Cluster 2 green	ai input; ai investment; ai technology; application; company; corporate esg performance; digital finance; digital transformation; effect; empirical evidence; enterprise; firm; heterogeneity analysis; impact; implementation; industry; investment; labor demand; mechanism analysis; micro enterprise; paper; strategy	AI Investment & Firm-Level Heterogeneity
Cluster 3 blue	business; focus; gic; green innovation performance; green intellectual capital; innovation; research; tacit knowledge; technology	Green Intellectual Capital & Innovation
Cluster 4 Yellow	ai application; artificial intelligence; artificial intelligence application; china; economy; medium sized enterprise; perspective; productivity; service industry	AI Application & Service Productivity in China

Cluster 2 AI Investment and Firm-Level Heterogeneity. This empirically oriented stream employs panel data methods and difference-in-differences designs to examine differential impacts of AI investment across firm types, industries, and economic contexts. Huang et al. (2026) demonstrate that corporate AI investment generates skill-biased structural adjustment, increasing technical employee proportions while reducing non-technical roles, with financing constraints amplifying negative employment effects, particularly among SMEs. Xie and Wu (2025) find that AI application enhances corporate ESG performance among Chinese listed firms by strengthening green technology innovation and philanthropic responsibility, while paradoxically weakening governance through reduced internal control effectiveness. Zhou and Ji (2026) show that digital finance enhances new-quality productivity through alleviating financing constraints, accelerating digital transformation and AI adoption, and strengthening innovation returns. Marcineková et al. (2025) provide qualitative evidence that even micro-enterprises can achieve meaningful gains through AI chatbot implementation, including a 45.9% reduction in response time and a 14.5% increase in customer satisfaction, when implementation is context-sensitive. Xu et al. (2024) find that aggregate AI input effects on labor demand among Chinese small and micro enterprises are

statistically insignificant as substitution and creation effects offset each other, though substitution dominates in private, high-tech, and low-labor-intensity firms. AI investment outcomes are therefore deeply heterogeneous, shaped by firm size, ownership type, industry characteristics, and institutional environment (Hrbić, 2025; Ostapenko et al., 2026).

Cluster 3 Green Intellectual Capital and Innovation. This theoretically coherent cluster draws on the Natural Resource-Based View, Knowledge-Based View, and stakeholder theory to examine how green intellectual capital mediates the pathway from AI-related capabilities to innovation and sustainability outcomes. Mehmood et al. (2026) demonstrate that green intellectual capital mediates tacit knowledge sharing to innovation performance, with AI moderating the tacit knowledge-GIC relationship and resource commitment strengthening the GIC-innovation link, positioning AI as a boundary-spanning enabler that amplifies existing knowledge assets rather than a direct driver of innovation. Dinh et al. (2026), through PLS-SEM of 431 Vietnamese SMEs, confirm that green intellectual capital significantly enhances green innovation and sustainable performance across environmental, social, and economic dimensions, though AI does not significantly moderate the green innovation-performance relationship, suggesting that AI's role is contingent on digital readiness and complementary process integration. Ahmed et al. (2026) demonstrate that AI-enabled talent acquisition and sustainable entrepreneurial orientation drive sustainable business performance through sequential mediation via environmental innovation capability and sustainable human capital agility, with environmental uncertainty moderating the eco-innovation pathway. Collectively, these studies position AI as an organizational capability whose sustainability value derives from integration with green intellectual capital, knowledge management, and innovation ecosystems (Crocco et al., 2025).

Cluster 4 AI Application and Service Productivity in China. This geographically specific stream employs panel fixed-effects models, instrumental variable approaches, and text-analysis-based AI measurement to examine AI-productivity relationships in the Chinese economy. Wu and Zhu (2025) establish that AI application positively affects total factor productivity of Chinese service firms, with modern service firms, SMEs, and state-owned enterprises achieving the most pronounced gains through increased R&D investment and optimized human capital allocation. Zhang and Li (2026) demonstrate that AI applications promote high-quality innovation among listed SMEs through horizontal and vertical external effects, operating by breaking path dependencies, promoting cross-border knowledge integration, and enhancing R&D efficiency, with stronger effects in high-knowledge-stock, competitive, and digitally mature firms. Yu and Qi (2025), analyzing 3,646 Chinese A-share companies, confirm that AI applications enhance enterprise productivity primarily by upgrading human capital through increasing highly educated employee proportions while displacing low-skilled workers. Zhang and Peng (2025) find that AI enhances productivity of Specialized, Refined, Unique, and Innovative SMEs by 6.82% per standard deviation increase, mediated by labor structure optimization, innovation stimulation, and management efficiency improvement. Productivity benefits are further differentiated by firm lifecycle stage (Wu & Zhou, 2026), firm size (Dong et al., 2025), and institutional characteristics, carrying direct policy implications for AI-oriented digital economy strategies in China and comparable emerging market contexts.

3.3. Antecedent, Mediators/Moderators, and Outcomes (AMMO) Framework

Drawing on the 29 included studies, this review organizes salient variables into an AMMO framework consistent with Zahoor et al. (2020) and applied in prior bibliometric reviews (Anggadwita & Indarti, 2023), enabling researchers to trace pathways through which AI-related inputs generate firm-level outcomes (Figure 10).

3.3.1 Antecedents

AI Adoption and Engagement. Studies drawing on the TOE framework and TAM identify the conditions under which firms initiate and sustain AI adoption. Badghish and Soomro (2024) identify relative advantage, compatibility, sustainable human capital, market demand, and government

Vol. 02 Year 2026, Hal 1886 – 1906
ISSN: 3309 - 3337

support as influential TOE dimensions, with firm size as a significant moderator. Haq et al. (2025) demonstrate that perceived ease of use, perceived usefulness, and organizational readiness are primary drivers of Green AI adoption among Pakistani manufacturing SMEs, with green investment mediating and green servant leadership moderating the adoption-performance pathway. Rahmani et al. (2026) extend TAM with a Resource-Based View perspective to find that AI usage intensity does not directly translate into business performance, pointing to the critical role of complementary resources. Alkhodair and Alkhudhayr (2025) confirm that Industry 4.0 adoption significantly enhances operational and strategic performance, though effect magnitude varies considerably by enterprise size and sector.

AI Capabilities and Resources. drawing on Dynamic Capabilities Theory and the Knowledge-Based View, conceptualizes AI-enabled knowledge capabilities as critical dynamic capabilities driving new product performance through direct and indirect pathways. Ratanacharoenchai and Jantapoon (2026) frame AI capabilities as sensing, seizing, and reconfiguring processes that enhance supply chain resilience as the primary mediating pathway. Ahmed et al. (2026) examine AI-enabled talent acquisition as an organizational antecedent demonstrating cascading effects on environmental innovation capability and sustainable human capital agility. Bushati et al. (2025) identify individual-level AI familiarity as a significant predictor of adoption intention, while Dong et al. (2025) trace differential growth effects of AI technology accessibility across firm sizes in the United States.

AI Applications and Innovation. Corporate AI investment, measured through keyword frequency analysis of annual reports and patent disclosures, is examined by Huang et al. (2026) and Xu et al. (2024) regarding effects on employment structure and labor demand. Zhang and Li (2026) and Zhang and Peng (2025) employ firm-level AI application indices to demonstrate that AI engagement promotes high-quality innovation and enterprise productivity, mediated by knowledge externalities, human capital optimization, and R&D efficiency.

3.3.2 Mediators and Moderators

Mediators. Innovation and transformation mechanisms constitute the most frequently examined mediating pathway. Environmental innovation capability mediates between AI-enabled talent acquisition and sustainable business performance (Ahmed et al., 2026), while digital product innovation radicalness mediates the AI-enabled knowledge capabilities to new product performance relationship (Dinh, 2026). Green innovation mediates the pathway from green intellectual capital to sustainable performance across environmental, social, and economic dimensions (Dinh et al., 2026), and digital transformation amplifies productivity returns of digital finance investments by accelerating AI adoption (Zhou & Ji, 2026).

Human capital and knowledge mechanisms represent a second mediating cluster. Anjum et al. (2026) establish knowledge management and intellectual capital as sequential mediators linking Generative AI adoption to sustainable organizational performance, with competitive advantage as the final mediating link. Human capital upgrading mediates the AI-productivity relationship in Chinese enterprises (Yu & Qi, 2025), while green intellectual capital components mediate the tacit knowledge-innovation performance pathway (Mehmood et al., 2026). Operational mechanisms including supply chain resilience fully mediate the AI capabilities-social sustainability relationship among Thai manufacturing SMEs, with variance accounted for reaching 69.7% (Ratanacharoenchai & Jantapoon, 2026). Financial and investment mechanisms including R&D investment, financing constraints, and green investment are documented primarily in Chinese firm-level studies (Haq et al., 2025; Huang et al., 2026; Zhou & Ji, 2026).

Moderators. Organizational characteristics, including firm size, lifecycle stage, implementation maturity, and industry context, consistently emerge as moderators. Ratanacharoenchai and Jantapoon (2026) demonstrate through multi-group analysis that smaller firms and early-stage implementers exhibit distinct capability-performance relationships. Firm size plays a central moderating role in Badghish and Soomro (2024), while Rahmani et al. (2026) find that firm size directly predicts performance independently of AI usage intensity.

Leadership and managerial orientation have been conceptualized as moderators in supply chain and sustainability contexts. Rankl and Nemeth (2026) propose managerial attitude as a behavioral amplifier within a Cobb-Douglas production framework, while green servant leadership moderates the organizational readiness-Green AI adoption relationship (Haq et al., 2025). Digital sustainability leadership is identified by Dinh (2026) as a boundary condition that fundamentally reconfigures how AI generates value in resource-constrained environments. Environmental uncertainty moderates the environmental innovation capability pathway, suggesting eco-innovation is most effective in turbulent markets (Ahmed et al., 2026). Financing constraints moderate the AI investment-employment structure relationship (Huang et al., 2026). Perceived organizational support is found to negatively moderate the Generative AI-knowledge management relationship, suggesting that excessively high support may induce overreliance on AI-generated knowledge while reducing employees' critical engagement (Anjum et al., 2026).

3.3.3 Outcomes

Economic and Financial Performance. Total factor productivity is positively and significantly predicted by AI application among Chinese service firms, particularly in modern service firms, SMEs, and state-owned enterprises (Wu & Zhu, 2025). Enterprise productivity is enhanced by AI applications in SRUI SMEs (Zhang & Peng, 2025) and Chinese listed companies broadly (Yu & Qi, 2025). New-quality productivity is significantly enhanced by digital finance with AI adoption functioning as a key transmission channel (Zhou & Ji, 2026). Financial performance indicators including net profit margin, return on assets, and business efficiency are documented in Croatian SMEs (Hrbić, 2025), while revenue growth, cost reduction, and return on investment are identified in Ukrainian enterprises undergoing digital transformation (Ostapenko et al., 2026).

Organizational and Business Performance. Sustainable business and organizational performance represent dominant outcome constructs in Cluster 1 studies. Badghish and Soomro (2024) decompose SME performance into operational and economic dimensions, while Anjum et al. (2026) establish sustainable organizational performance as the ultimate outcome of a sequential knowledge-driven process. New product performance is examined by Dinh (2026) as the primary outcome of AI-enabled knowledge capabilities, and supply chain flexibility and responsiveness are proposed as outcomes of managerial attitude-amplified AI integration (Rankl & Nemeth, 2026).

Sustainability and ESG Outcomes. Corporate ESG performance is significantly enhanced by AI technology application, improving environmental performance through green technology innovation and social performance through philanthropic responsibility, while weakening governance through reduced internal control effectiveness (Xie & Wu, 2025). Carbon emission intensity is reduced by AI adoption primarily in growth-stage enterprises through productivity and innovation mechanisms (Wu & Zhou, 2026). Green innovation performance is enhanced by AI adoption mediated by green intellectual capital (Crocco et al., 2025; Dinh et al., 2026).

Innovation and Capability Outcomes. High-quality innovation measured through patent citation counts is established as the primary outcome of AI application in Chinese listed SMEs (Zhang & Li, 2026), while innovation performance is identified as the ultimate outcome of a GIC-mediated tacit knowledge sharing process (Mehmood et al., 2026). Li et al. (2020) document an inverted U-shaped relationship between AI firm innovation performance and probability of receiving public innovation funding, moderated by social investment and institutional intermediary ties.

Human Capital and Employment Outcomes. Corporate AI investment generates skill-biased structural adjustment, increasing technical employee proportions while reducing non-technical roles, with effects amplified by financing constraints in SMEs (Huang et al., 2026). Net AI impact on overall labor demand among Chinese small and micro enterprises is statistically insignificant as substitution and creation effects cancel out, though substitution dominates in private, high-tech, and low-labor-intensity enterprises (Xu et al., 2024). Customer satisfaction, growth, and organizational reputation are identified as additional business performance indicators (Badghish & Soomro, 2024; Ha et al., 2026), while customer service response time and monthly inquiry volume are documented as operational outcomes of AI chatbot implementation in micro-enterprises (Marcineková et al., 2025).

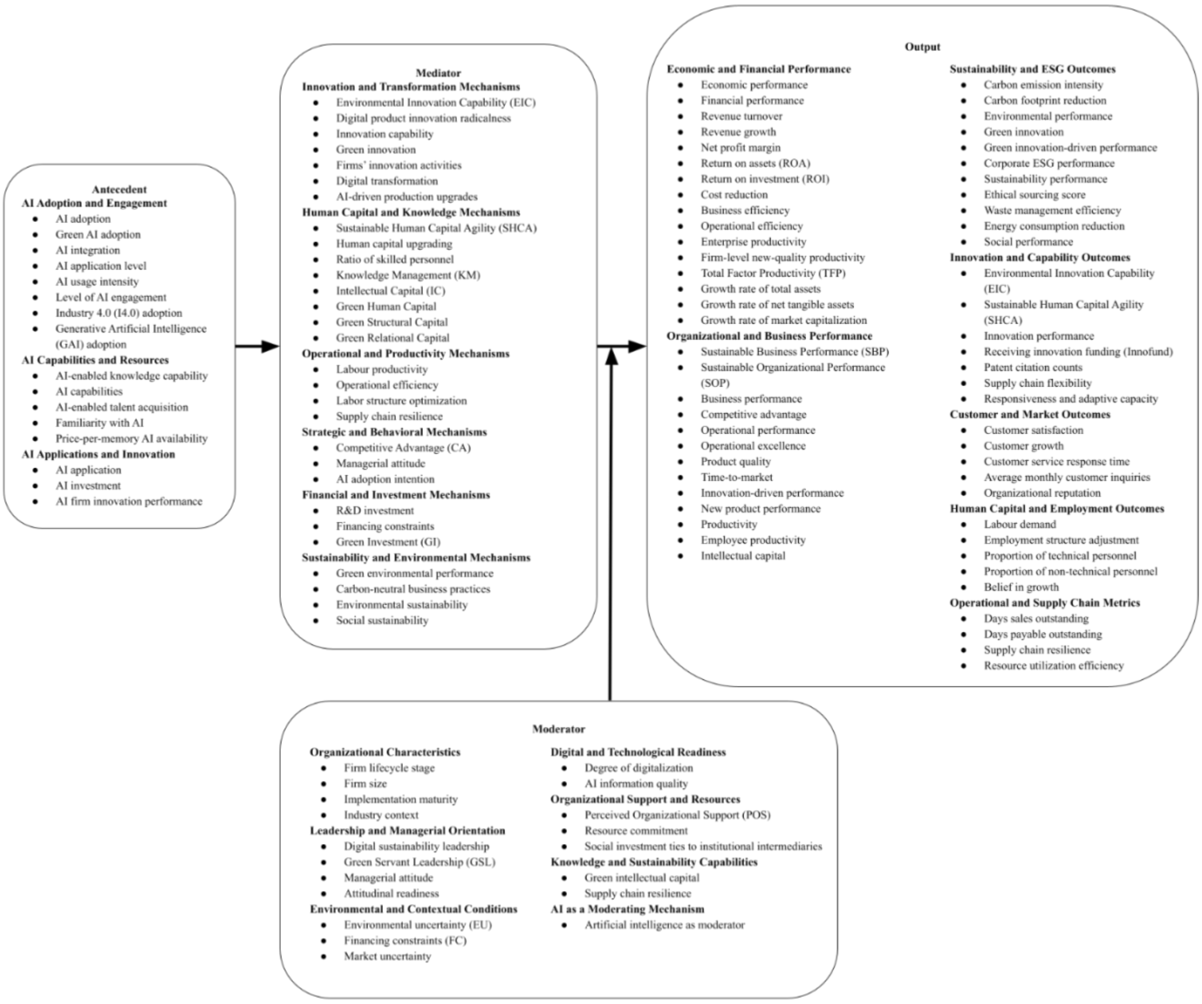

Figure 8 Antecedent, Mediation, Moderator, Output (AMMO) Framework

CONCLUSIONS, IMPLICATIONS AND LIMITATIONS

Conclusions

This systematic literature review addressed two central questions: why AI adoption outcomes remain heterogeneous across SMEs, and through what organizational mechanisms AI creates business value in these contexts. Drawing on 29 peer-reviewed articles retrieved from Scopus and published between 2020 and 2026, the review synthesized the literature through bibliometric mapping and qualitative content analysis, yielding four thematic clusters and an integrative AMMO framework.

Regarding the first research question, evidence across the four clusters converges on the conclusion that AI adoption outcomes are heterogeneous because value creation through AI is neither direct nor deterministic, but contingent upon organizational, contextual, and institutional boundary conditions. Firm size, implementation maturity, industry sector, ownership type, financing constraints, and digital readiness consistently emerge as moderating variables that reconfigure the magnitude and direction of the AI-performance relationship. The dominant techno-optimistic assumption framing AI adoption as a direct pathway to superior organizational performance is therefore empirically unsustainable as a universal proposition. The literature demonstrates instead that AI functions as a conditional strategic resource whose value is co-produced by the organizational capabilities brought to bear upon its deployment.

Regarding the second research question, the review identifies five categories of organizational mechanisms through which AI creates business value in SMEs: innovation and transformation mechanisms, human capital and knowledge mechanisms, operational and productivity mechanisms, strategic and behavioral mechanisms, and financial and investment mechanisms. Knowledge-mediated pathways involving knowledge management, intellectual capital, and green intellectual capital constitute the most theoretically developed stream, drawing on the Resource-Based View and Dynamic Capabilities Theory to explain how AI-generated knowledge flows are converted into competitive advantage and sustainable organizational performance. Innovation mechanisms, including digital product innovation radicalness, environmental innovation capability, and green innovation, represent a rapidly emerging stream positioning AI as an organizational enabler of eco-innovation rather than a direct performance driver. Human capital mechanisms, particularly skill-biased structural adjustment and upgrading of employee educational composition, are consistently documented in firm-level studies from China, pointing to labor market transformation as a critical and often underappreciated productivity pathway.

Taken together, the findings establish that the AI-performance relationship in SMEs is best understood through a process-oriented and organizationally embedded lens rather than a techno-deterministic one. The AMMO framework provides an integrative scaffolding mapping antecedents, mediating mechanisms, moderating conditions, and performance outcomes across multiple levels of analysis, thereby advancing the field beyond fragmented outcome-oriented perspectives. The literature nonetheless remains in a formative stage: nearly 90% of reviewed publications appeared in 2025 and 2026, geographic coverage is heavily skewed toward China and a limited set of developing economy contexts, and the predominance of cross-sectional survey designs limits causal inference.

Implications

Theoretical Implications. This review makes three principal theoretical contributions. First, by systematically demonstrating that AI adoption outcomes are conditioned by organizational capabilities and institutional contexts rather than by the technology itself, the study challenges techno-deterministic assumptions that have dominated the field's early phase and calls for a capability-contingent theoretical perspective. Future theory development should engage more explicitly with institutional theory, organizational learning theory, and complexity theory to account for the path-dependent and non-linear nature of AI value creation in resource-constrained firms.

Second, the AMMO framework contributes a structured multilevel conceptual architecture that integrates antecedents, mediating mechanisms, moderating conditions, and performance outcomes into a single coherent model, explicitly accounting for the processual and contingency dimensions of AI-enabled value creation. Future theoretical work should empirically test and refine cross-level interactions within this framework, particularly those linking individual-level AI familiarity and managerial orientation to organizational-level performance outcomes.

Third, the emergence of green intellectual capital and sustainability-oriented mechanisms as a significant thematic cluster signals a theoretical convergence between the AI-performance literature and the Natural Resource-Based View and stakeholder theory traditions, opening productive territory in which AI is conceptualized as a sustainability capability mediating between knowledge-based assets and environmental and social performance outcomes.

Managerial Implications. The central practical implication is that AI investment value is not automatic and cannot be realized through technology adoption alone. Sustainable performance gains require deliberate investment in organizational complements: knowledge management infrastructure, data governance, human capital development, and dynamic sensing and reconfiguring capabilities. Managers who treat AI adoption as a plug-and-play operational solution risk the performance paradox documented by several reviewed studies, wherein AI usage intensity fails to translate into measurable business improvement.

Vol. 02 Year 2026, Hal 1886 – 1906
ISSN: 3309 - 3337

The human capital stream carries a specific managerial warning: AI investment generates skill-biased structural adjustments that increase demand for technically proficient employees while reducing roles susceptible to automation. SME managers must anticipate workforce transition challenges and invest proactively in reskilling and upskilling programs to prevent the erosion of organizational knowledge capital, a concern especially critical for micro-enterprises and family businesses in which tacit knowledge is concentrated in a small number of individuals. For SMEs subject to growing ESG reporting expectations, green intellectual capital functions as the primary conduit through which AI-related investments generate green innovation and sustainable performance outcomes. Managers seeking to leverage AI for ESG performance improvement should prioritize development of green human capital and cultivation of sustainability-oriented external knowledge networks before deploying AI in environmental or social performance domains.

Policy Implications. For policymakers, the findings underscore the importance of moving beyond AI diffusion programs toward ecosystem-level interventions addressing organizational capability constraints. Subsidizing AI tool acquisition without simultaneously investing in managerial capability development, data infrastructure, and digital literacy is unlikely to generate targeted productivity and sustainability outcomes. Integrated support programs bundling AI adoption assistance with knowledge management consulting, workforce development funding, and access to green finance are more likely to produce sustainable performance improvements across the SME population.

The digital finance stream additionally points to the strategic role that financial ecosystem development plays in enabling AI-driven productivity growth. Policymakers in emerging economies should attend to financing constraints that disproportionately affect small and micro-enterprises, private firms, and labor-intensive industry operators, as these constraints amplify distributional inequities of AI adoption. Targeted financial instruments reducing AI investment costs for resource-constrained SMEs represent a high-leverage policy intervention with both economic and social returns.

Limitations

Five limitations circumscribe this study's scope and generalizability. First, exclusive reliance on Scopus potentially introduces selection bias by excluding relevant contributions indexed in Web of Science, Google Scholar, EBSCO, or ProQuest, particularly those representing emerging economy contexts. Future reviews should adopt multi-database search protocols.

Second, the final corpus of 29 articles, while reflecting the genuinely nascent state of the field, limits bibliometric statistical power and constrains cross-study comparisons. With approximately 90% of publications concentrated in 2025 and 2026, the literature has not yet been subjected to extensive replication or theoretical consolidation, and the conclusions advanced here should be understood as provisional syntheses of an emerging literature rather than definitive characterizations of a mature field.

Third, the geographic distribution is heavily skewed toward China, whose institutional, regulatory, and market characteristics differ substantially from Southeast Asian, Sub-Saharan African, Latin American, and European SME populations, limiting the transferability of mechanism-level findings and constituting a significant boundary condition on the generalizability of the AMMO framework.

Fourth, the predominance of cross-sectional survey designs and single-country panel datasets leaves the causal directionality of most documented relationships unconfirmed. The mechanisms through which AI creates organizational value are inherently dynamic and temporally extended, yet the field's heavy reliance on PLS-SEM raises concerns about common method variance and the conflation of mediating mechanisms that may operate sequentially over multiple time periods. Future research should prioritize longitudinal and mixed-method designs.

Fifth, terminological inconsistency across the reviewed literature, wherein SME, MSME, micro-enterprise, and small firm are used interchangeably without consistent definitional

Vol. 02 Year 2026, Hal 1886 – 1906
ISSN: 3309 - 3337

grounding, obscures important heterogeneity in how AI adoption unfolds across firm size categories. Future research should adopt more precise and contextually grounded firm size classifications to enable more granular and policy-relevant insights.

This study provides the first systematic synthesis of the AI adoption and SME performance literature and advances a multilevel AMMO framework as a theoretical foundation for future empirical and conceptual inquiry. The limitations identified herein define a clear and productive agenda for the next generation of scholarship on AI-enabled organizational transformation in resource-constrained entrepreneurial contexts.

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Vol. 02 Year 2026, Hal 1886 – 1906
ISSN: 3309 - 3337

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