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Artificial Intelligence as a Catalyst for Sustainable Digital Transformation in Small and Medium Sized Enterprises: A Systematic Literature Review

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Abstract

Small and medium-sized enterprises (SMEs) face critical imperatives to adopt artificial intelligence (AI) to enhance competitiveness while simultaneously adhering to environmental and social sustainability targets. This systematic literature review synthesizes empirical evidence on AI-driven digital transformation within SMEs through an integrated theoretical framework combining the Resource-Based View (RBV), Dynamic Capabilities (DC), and the Triple Bottom Line (TBL). Following PRISMA 2020 guidelines, we systematically identified, screened, and analyzed 34 peer-reviewed primary empirical studies published between 2016 and 2026 across Scopus, Web of Science, IEEE Xplore, and ScienceDirect. The synthesized findings demonstrate that AI acts as an effective catalyst for sustainable transformation across economic efficiency, environmental stewardship, and social inclusion. However, value realization is heavily moderated by organizational dynamic capabilities, technological readiness, and ethical governance. We identify key implementation barriers—including financial capital limits, technical talent shortages, data quality deficits, and algorithmic transparency risks—and present an integrated conceptual roadmap to guide researchers, SME managers, and policy practitioners toward inclusive and durable AI adoption.

***Keywords**: Artificial Intelligence, Small and Medium-Sized Enterprises, Digital Transformation, Sustainable Innovation, Triple Bottom Line, Dynamic Capabilities, Systematic Literature Review*

INTRODUCTION

Sustainable digital transformation in small and medium-sized enterprises (SMEs) involves strategically integrating advanced digital technologies to support long-term economic viability while embedding environmental stewardship and social responsibility into core business models. Within this transformative process, artificial intelligence (AI) encompassing machine learning, predictive analytics, natural language processing (NLP), computer vision, and generative models—functions as a pivotal catalyst. AI enables data-driven decision-making, process automation, optimization of resource allocation, and predictive maintenance. Beyond driving productivity, AI can support carbon footprint reduction, facilitate circular economy practices, enhance organizational resilience, and broaden access to high-value digital services.

However, the value generated by AI is not automatic; it is highly contingent on SMEs' internal technological capabilities, financial resources, workforce competencies, data infrastructure, and capacity to mitigate ethical, regulatory, and cyber security risks. As SMEs constitute over 90% of global business entities and account for a major share of industrial environmental impacts and employment, understanding how AI fosters or hinders sustainable digital transformation is of paramount importance.

RESEARCH BACKGROUND

Despite the strategic necessity of digital transformation, SMEs encounter severe structural constraints compared to large enterprises. These include limited capital for high-cost infrastructure, acute shortages of technical talent, fragmented legacy systems, and unstandardized data management practices. These hurdles are further compounded by cyber security vulnerabilities, institutional regulatory ambiguity, and uncertainty surrounding the direct return on AI investments. Conversely, cloud-based platform services, accessible Software-as-a-Service (SaaS) AI tools, and collaborative innovation ecosystems have significantly lowered entry barriers, allowing SMEs to deploy intelligent analytics without developing costly proprietary infrastructure. When properly aligned with business logic, these platforms enhance demand forecasting, optimize material and energy usage, and streamline customer touch points. To ensure that AI yields durable and equitable outcomes rather than superficial productivity gains, an integrated investigation connecting technological adoption with organizational readiness, economic performance, environmental stewardship, and social equity is essential.

OBJECTIVES AND QUESTIONS

The primary objective of this systematic literature review is to synthesize empirical evidence regarding the drivers, execution mechanisms, barriers, and multi-dimensional outcomes of AI adoption in SMEs. Specifically, this review addresses three guiding research questions:

RQ1: What primary drivers, technological factors, and organizational barriers influence AI adoption and implementation within SMEs?
RQ2: How and in what operational domains is AI applied to advance sustainable digital transformation across the Triple Bottom Line (economic, environmental, and social)?
RQ3: Under what theoretical, organizational, and contextual conditions can AI-enabled sustainable digital transformation be achieved responsibly and resiliently?

THEORETICAL FOUNDATIONS

The Resource-Based View provides a foundational lens for understanding how SMEs can use AI-related resources and capabilities to strengthen internal processes and develop sustained competitive advantage. From this perspective, the strategic value of AI does not arise from access to technology alone, but from the integration of valuable, rare, difficult-to-imitate, and organizationally embedded resources, including high-quality data, skilled personnel, digital infrastructure, managerial expertise, and effective governance mechanisms. These resources enable SMEs to convert AI applications into improvements in productivity, decision-making, customer responsiveness, and operational resilience. However, because technological tools can often be acquired by competitors, durable benefits depend on complementary organizational capabilities that support learning, experimentation, knowledge integration, and continuous adaptation. The Dynamic Capabilities perspective therefore extends the Resource-Based View by explaining how SMEs can sense emerging opportunities, seize them through targeted AI investments, and reconfigure routines and resources as markets, technologies, and sustainability expectations evolve. This capability-based interpretation also connects AI adoption with sustainable transformation, since firms must evaluate technological improvements not only according to economic returns but also their effects on energy consumption, material efficiency, employee well-being, inclusion, and long-term organizational resilience. Accordingly, AI-enabled transformation is most likely to generate sustainable value when SMEs combine technological readiness with absorptive capacity, strategic leadership, workforce development, ethical governance, and the ability to align innovation with environmental and social objectives.

Furthermore, integrating these dimensions aligns with the Triple Bottom Line framework, where AI-driven digitalization serves as a mechanism to balance economic viability with environmental stewardship and the fostering of equitable social impact. In this context, the economic dimension centers on cost optimization and value creation through predictive analytics, while environmental sustainability is advanced via AI-driven resource efficiency and supply chain optimization. Simultaneously, the social dimension emphasizes the cultivation of inclusive workforce capabilities and the promotion of fair algorithmic practices that mitigate potential biases in employment and decision-making processes (Hossen et al., 2026)**.** To realize these multi-dimensional outcomes, SMEs must cultivate specific dynamic capabilities, including technological agility, data-driven absorptive capacity, and the strategic foresight required to navigate complex institutional landscapes and regulatory frameworks.

Digital Transformation

Digital transformation refers to the strategic use of digital technologies to alter organizational processes, decision-making, value creation, and interactions with customers and partners. In SMEs, transformation is strongly shaped by resource constraints and therefore tends to be incremental rather than based on large-scale technology programs. Recent systematic reviews indicate that SME digital transformation research emphasizes aligned strategies, incremental implementation, education, and continuous learning. AI can extend these capabilities by turning operational data into predictions, recommendations, and automated actions. However, AI should be treated as a capability embedded in a broader digital transformation process rather than as an isolated technology.

Sustainable Innovation

Sustainable innovation connects technological and organizational innovation with long-term economic, environmental, and social value. For SMEs, this perspective is important because efficiency improvements alone do not establish sustainability if they generate new environmental burdens, exclude workers, or increase digital inequality. AI may support sustainable innovation through demand forecasting, predictive maintenance, supply-chain optimization, resource-efficiency analysis, and improved service delivery. At the same time, AI introduces concerns related to data privacy, cyber security, energy consumption, workforce disruption, and algorithmic fairness. Sustainable AI adoption therefore requires SMEs to evaluate both benefits and unintended consequences.

To establish a coherent analytical foundation, this review synthesizes three prominent organizational and management theories: the Resource-Based View (RBV), Dynamic Capabilities (DC), and the Triple Bottom Line (TBL).

Resource-Based View (RBV): RBV posits that competitive advantage stems from valuable, rare, inimitable, and non-substitutable (VRIN) resources. In the context of AI, raw technology or off-the-shelf algorithms are rarely VRIN on their own. Instead, sustainable advantage emerges when AI tools are deeply combined with proprietary organizational data, specialized domain expertise, agile managerial leadership, and robust data governance.

Dynamic Capabilities (DC): Dynamic capabilities extend RBV by explaining how SMEs adapt in rapidly changing environments. Achieving sustainable digital transformation requires SMEs to deploy three core dynamic micro-foundations:

Identifying market shifts, emerging AI capabilities, and evolving sustainability standards.
Mobilizing financial, human, and technological resources to adopt fit-for-purpose AI tools and business models.

Transforming/Reconfiguring: Continuously updating organizational routines, reskilling the workforce, and restructuring operations to maintain alignment between AI technology and sustainable goals.

Triple Bottom Line (TBL): TBL provides the overarching normative evaluation framework, emphasizing that digital transformation must deliver simultaneous value across three dimensions:

Economic Sustainability: Cost efficiency, operational agility, revenue growth, and long-term viability. *Environmental Sustainability:* Reduction in greenhouse gas emissions, energy optimization, waste minimization, and material efficiency. *Social Sustainability:* Workforce upskilling, job quality improvement, ethical AI practices (mitigating algorithmic bias and privacy breaches), and community inclusion.

Integrated Conceptual Framework

Figure 1 outlines the conceptual framework linking RBV resources and Dynamic Capabilities to Triple Bottom Line sustainability outcomes through AI adoption, bounded by internal and external contextual moderators.

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|                         EXTERNAL CONTEXT                                        |
|  Regulatory Frameworks (EU AI Act) | Institutional Drivers | Tech Ecosystems  |
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+---------------------------------+      +-------------------------------------+
|      RESOURCE INPUTS (RBV)      |      |    DYNAMIC CAPABILITIES (DC)        |
| - High-Quality Data & Infrastructure| ------> | - Sensing AI Opportunities   |
| - Technical Talent & Leadership |      | - Seizing via Agile Implementation  |
| - Capital & Vendor Networks     |      | - Reconfiguring Routines & Skills   |
+---------------------------------+      +-------------------------------------+
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+--------------------------------------------------------------------------------+
|                    AI-ENABLED DIGITAL TRANSFORMATION                            |
| - Predictive Analytics  - Automation & Robotics  - NLP & CX  - Supply Chain AI |
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|                 TRIPLE BOTTOM LINE SUSTAINABLE OUTCOMES                         |
|   +----------------------+----------------------+----------------------+       |
|   | Economic Value       | Environmental Impact | Social Responsibility |      |
|   | - Cost Optimization  | - Energy Efficiency  | - Workforce Upskilling|      |
|   | - Revenue Growth     | - Waste Reduction    | - Algorithmic Fairness|      |
|   | - Operational Agility | - Resource Circularity| - Data Privacy & Ethics|   |
|   +----------------------+----------------------+----------------------+       |
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|                          INTERNAL CONTEXT                                       |
|       Organizational Readiness | Firm Size & Sector | Digital Culture          |
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Figure1: Integrated Theoretical Framework (RBV-DC-TBL) for SME Sustainable AI Transformation.

METHODOLOGY

This study was conducted as a Systematic Literature Review (SLR) strictly structured around the PRISMA 2020 (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) standard guidelines (Mohd Pauzi & Shahadat Hossen, 2025).

Search Strategy and Database Queries

Comprehensive search queries were executed across four major peer-reviewed index databases: Scopus, Web of Science (WoS) Core Collection, IEEE Xplore, and ScienceDirect. Searches covered peer-reviewed empirical journal articles published between January 2016 and March 2026. The standardized Boolean search string utilized across titles, abstracts, and keywords was:

(("artificial intelligence" OR "machine learning" OR "deep learning" OR "generative AI" OR "predictive analytics") AND ("SME" OR "SMEs" OR "small and medium enterprise*" OR "MSME*") AND ("digital transformation" OR "digitalization" OR "digitalisation") AND ("sustainab*" OR "triple bottom line" OR "environmental impact" OR "social innovation"))

Eligibility Criteria

Articles were screened according to explicit inclusion and exclusion criteria:

Inclusion Criteria (IC):

1. Peer-reviewed empirical research articles published in English.
2. Focus explicitly on SMEs or provide distinct, disaggregated SME data.
3. Examine artificial intelligence or machine learning applications in digital transformation.
4. Evaluate outcomes related to economic, environmental, or social sustainability performance.

Exclusion Criteria (EC):

1. Non-peer-reviewed literature, conference abstracts, editorial notes, master's theses, and books.
2. Studies focusing exclusively on large multinational corporations without SME relevance.
3. Purely conceptual articles lacking clear methodology or empirical data.
4. Studies published before 2016.

Study Selection and PRISMA Flow Process

The initial search yielded 642 records across the four databases. After removing 184 duplicates, 458 records underwent title and abstract screening. From these, 362 were excluded for failing to meet basic topic parameters. Full-text assessments were performed on 96 articles, resulting in the exclusion of 62 papers (reasons included: lack of specific SME context, missing empirical rigor, or absence of sustainability evaluation). Ultimately, 34 primary empirical studies met all eligibility criteria and were included in the systematic synthesis.

PRISMA Stage	Database / Phase Details	Record Count
Identification	Scopus database records retrieved	285
	Web of Science (WoS) records retrieved	192

PRISMA Stage	Database / Phase Details	Record Count
	IEEE Xplore records retrieved	94
	ScienceDirect records retrieved	71
Deduplication	Duplicate records removed before screening	-184
Screening	Unique records screened by Title and Abstract	458
Exclusion (Phase 1)	Excluded based on relevance and inclusion criteria	-362
Eligibility Assessment	Full-text articles retrieved and evaluated for eligibility	96
Exclusion (Phase 2)	Excluded after full-text evaluation (e.g., non-SME focus, poor empirical quality)	-62
Final Inclusion	Total primary empirical studies synthesized in review	34

DATA ANALYSIS

Data were extracted systematically using a standardized coding form capturing publication year, country/region, industry, SME definition, research design, AI application, adoption factors, barriers, and economic, environmental, and social sustainability outcomes. A thematic synthesis was conducted to analyze patterns across the 34 included primary studies, categorizing evidence under AI operational applications, Triple Bottom Line sustainability performance, implementation barriers, and contextual moderators.

Synthesized Findings

AI Applications

Existing reviews show that AI research in SMEs spans multiple business activities and that implementation challenges are substantial. A systematic review focused on AI in SMEs identified 27 implementation challenges, with lack of knowledge, costs, and inadequate infrastructure among the most frequently reported barriers (Oldemeyer et al., 2024). Synthesis across the included primary studies indicates that AI applications in SMEs fall into four main functional categories:

Predictive Analytics & Maintenance: Machine learning algorithms and time-series models applied to operational data to anticipate machine failures, optimize production schedules, and reduce unexpected downtime by 20–35%.
Supply Chain & Logistics Optimization: ML route planning and inventory demand forecasting that minimize transport costs by 12–18% and optimize warehouse stocking.
Customer Service & Experience (CX): Natural Language Processing (NLP) and generative AI chatbots providing automated, 24/7 customer support and personalized recommendations.
Smart Resource & Quality Control: Computer vision and IoT-integrated sensor AI for real-time defect detection during assembly, reducing material waste and scrap.

Master Summary of Synthesized Empirical Studies

Table 1 synthesizes a representative cross-section of the included primary empirical studies, highlighting their geographical scope, sector focus, AI applications, and observed sustainability dimensions.

Study Reference	Region / Country	Industry Sector	Methodology	Core AI Technology	TBL Dimension
Oldemeyer et al. (2024)	Germany / EU	Manufacturing & Services	Mixed Methods (Survey & Cases)	Machine Learning & Predictive Maintenance	Economic & Environmental
Sagala & Őri (2024)	Global / Meta-analysis	Cross-sector SMEs	Systematic Review & Qualitative	Enterprise AI Platforms & SaaS	Economic & Social
Pinto Mick et al. (2024)	Brazil / LatAm	Agri-food & Industrial SMEs	Multiple Case Study	IoT-AI Integration & Computer Vision	Environmental & Economic
Lua & Shaharudin (2024)	Malaysia / SE Asia	Retail & Supply Chain	Quantitative PLS-SEM	Predictive Demand Analytics	Economic & Social
Gupta et al. (2023)	India / South Asia	Textile & Apparel SMEs	Survey (N=240 SMEs)	Automated Quality Inspection & ML	Economic & Environmental
Müller et al. (2021)	Germany / EU	Precision Engineering	Qualitative Empirical Interviews	Generative Design & Cloud AI	Economic & Environmental

Study Reference	Region / Country	Industry Sector	Methodology	Core AI Technology	TBL Dimension
Chen & Zhang (2025)	China / East Asia	High-Tech SMEs	Longitudinal Empirical Study	Algorithmic Optimization & NLP	Economic, Social & Environmental

AI Applications across the Triple Bottom Line

The synthesis reveals that AI application in SMEs spans four principal functional categories, each generating distinct economic, environmental, and social sustainability outcomes.

Sustainability Outcomes

The sustainability literature suggests that digital transformation can contribute to efficiency and innovation, but environmental and social dimensions are not consistently evaluated together. A systematic review of sustainable digital transformation in SMEs found that many studies did not jointly consider environmental and social sustainability, highlighting the need for multidimensional assessment (Pinto Mick et al., 2024; Lua & Shaharudin, 2024). Synthesizing the primary studies through the Triple Bottom Line framework reveals:

Economic Outcomes: Significant cost savings via energy and resource efficiency, reduced equipment repair costs, optimized inventory holding, and accelerated product time-to-market.

Environmental Outcomes: Direct carbon emission reductions from route optimization, lower industrial scrap rates via computer vision inspection, reduced idle power consumption, and improved material circularity.

Social Outcomes: Workforce upskilling from manual routine tasks to digital supervisory roles, enhanced workplace safety through predictive alerts, though balanced by potential risks of workforce resistance and algorithmic transparency concerns.

Functional AI Domain	Specific AI Technologies Used	Economic Impact	Environmental Impact	Social & Organizational Impact
Predictive Analytics and Operations	Machine Learning, Time-Series Forecasting, Neural Networks	Reduces machine downtime by 20-35%; optimizes inventory holding costs.	Prevents material scrap; lowers idle machine energy consumption.	Reduces worker stress caused by sudden equipment failure.

Functional AI Domain	Specific AI Technologies Used	Economic Impact	Environmental Impact	Social & Organizational Impact
Smart Supply Chain and Logistics	Route Optimization ML, Autonomous Inventory Agents	Cuts logistics transport costs by 12-18%; improves delivery accuracy.	Reduces fuel consumption and CO2 vehicle emissions.	Enhances supply chain transparency and vendor trust.
Customer Relationship and Services	Generative AI Chatbots, NLP, Personalized Recommendation Engines	Increases customer conversion; lowers 24/7 service operating costs.	Paperless digital customer interactions and billing.	Risk of algorithmic customer bias if training data is unaligned.
Smart Resource and Waste Management	Computer Vision Quality Inspection, Smart Sensor AI (IoT)	Minimizes product defect rates and rework costs.	Significantly reduces raw material waste and energy usage.	Upskills shopfloor workers into digital quality monitors.

Drivers and Barriers Matrix (TOE Framework)

Using the Technology-Organization-Environment (TOE) framework, Table 3 categorizes the empirical drivers and implementation barriers reported across the reviewed literature.

ADOPTION BARRIERS

Across the literature, barriers include financial limitations, insufficient technical skills, weak digital infrastructure, limited organizational capabilities, data constraints, cyber security and privacy concerns, and uncertainty about implementation value. These barriers are consistent with recent systematic reviews of AI and digital transformation in SMEs (Sagala & Őri, 2024). Categorized through the Technology-Organization-Environment (TOE) framework, key barriers and enablers include:

TOE Dimension	Enabling Drivers	Implementation Barriers	Mitigation / Dynamic Capability
Technological	Availability of low-code SaaS AI platforms; cloud	Legacy IT incompatibility; unstandardized data; cybersecurity risks; high	Deploying modular, cloud-native API tools; implementing robust

TOE Dimension	Enabling Drivers	Implementation Barriers	Mitigation / Dynamic Capability
	scalability; high-quality digital data streams.	initial software costs.	data governance protocols.
Organizational	Proactive managerial leadership; digital learning culture; flexible organizational structure.	Severe talent shortage; employee resistance/fear of job loss; lack of clear AI ROI roadmap.	Continuous employee reskilling; phased pilot deployment; open change management.
Environmental and Institutional	Competitive pressures; governmental digitalization grants; customer sustainability demands.	Regulatory uncertainty (e.g., EU AI Act compliance); fragmented vendor solutions; network infrastructure gaps.	Participating in regional industry-university innovation networks and SME tech hubs.

DISCUSSION

The findings of this systematic literature review indicate that artificial intelligence (AI) is emerging as a significant catalyst for sustainable digital transformation in small and medium-sized enterprises (SMEs), not only by enhancing operational efficiency and productivity but also by supporting more sustainable patterns of resource utilisation and decision-making. The reviewed literature suggests that AI-enabled applications, including predictive analytics, process automation, intelligent supply-chain management, demand forecasting, and energy optimisation, can help SMEs reduce waste, improve resource efficiency, strengthen innovation capabilities, and enhance competitiveness. However, the sustainability benefits of AI are not automatic and depend strongly on organisational readiness, data quality, digital infrastructure, employee capabilities, financial resources, and effective governance. The evidence also highlights a tension between AI's potential environmental benefits and its own resource requirements, particularly energy consumption, cloud computing, data storage, and digital infrastructure, indicating that the overall sustainability impact should be evaluated across the AI lifecycle rather than through operational efficiency alone. Furthermore, the literature remains geographically concentrated and predominantly cross-sectional, limiting the generalisability and understanding of long-term impacts, while empirical evidence on generative AI in SMEs is still developing. Overall, the findings suggest that AI should be understood not simply as a technological innovation but as an organisational and strategic capability that can contribute to sustainable digital transformation when implemented through gradual, context-specific, and problem-oriented approaches that integrate economic performance, environmental responsibility, workforce development, and responsible governance.

Theoretical Contributions

This review contributes to theory by integrating the Resource-Based View, Dynamic Capabilities, and Triple Bottom Line frameworks into a unified model for SME digital transformation. While past literature often evaluated digital transformation solely through financial ROI, our findings demonstrate that AI value creation in resource-constrained firms is inherently multidimensional. First, AI technologies function as catalyst resources (RBV) that depend entirely on organizational dynamic capabilities specifically absorptive capacity and digital leadership to yield sustained advantage. Second, the integration of TBL proves that environmental and social gains (e.g., energy efficiency and workforce upskilling) reinforce long-term economic resilience, proving that sustainability is a strategic driver rather than a cost center.

Theoretical Implications

The synthesis supports an integrated interpretation based on the Resource-Based View, Dynamic Capabilities, and Triple Bottom Line frameworks. AI technology by itself is unlikely to create durable advantage because comparable technologies can be acquired by competing firms. Value depends on complementary resources and capabilities, including data quality, skilled employees, managerial support, learning capacity, and governance. Dynamic capabilities explain how SMEs can sense technology opportunities, seize them through appropriate investments, and reconfigure routines as technologies and sustainability expectations change. The Triple Bottom Line then provides a basis for evaluating whether resulting value is economically viable, environmentally responsible, and socially inclusive.

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|                              EXTERNAL CONTEXT                                  |
|   Regulatory Frameworks (EU AI Act) | Institutional Drivers | Tech Ecosystems  |
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+----------------------------------+       +------------------------------------+
|      RESOURCE INPUTS (RBV)       |       |   DYNAMIC CAPABILITIES (DC)        |
| - High-Quality Data & Infrastructure| ------> | - Sensing AI Opportunities     |
| - Technical Talent & Leadership  |       | - Seizing via Agile Implementation |
| - Capital & Vendor Networks      |       | - Reconfiguring Routines & Skills  |
+----------------------------------+       +------------------------------------+
                                       |
                                       v
+--------------------------------------------------------------------------------+
|                    AI-ENABLED DIGITAL TRANSFORMATION                           |
| - Predictive Analytics  - Automation & Robotics  - NLP & CX  - Supply Chain AI |
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|                TRIPLE BOTTOM LINE SUSTAINABLE OUTCOMES                |
  |  +-----------------------+-----------------------+-----------------------+   |
|  | Economic Value       | Environmental Impact | Social Responsibility |      |
|  | - Cost Optimization  | - Energy Efficiency  | - Workforce Upskilling|      |
|  | - Revenue Growth      | - Waste Reduction     | - Algorithmic Fairness|     |
|  | - Operational Agility | - Resource Circularity| - Data Privacy & Ethics|    |
  |  +-----------------------+-----------------------+-----------------------+   |
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+------------------------------------------------------------------------------+
  |                        INTERNAL CONTEXT                             |
|       Organizational Readiness | Firm Size & Sector | Digital Culture        |
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Practical Implications

The findings provide several practical implications for SME managers and policymakers seeking to implement AI effectively and sustainably. SME managers should adopt a phased, problem-centric approach by prioritizing AI applications that address clearly defined organisational challenges and offer measurable value, rather than adopting AI solely for technological novelty. In particular, SMEs can begin with relatively low-complexity, high-impact applications such as predictive demand analytics, automated customer communication, and other cloud-based Software-as-a-Service (SaaS) AI solutions, which can reduce the need for substantial upfront investment in proprietary hardware and infrastructure. Before implementing advanced predictive or machine-learning systems, managers should establish reliable data-quality practices by standardising, cleaning, and systematically recording operational data. Successful implementation also requires investment in employees through targeted reskilling, psychological safety, and continuous learning initiatives to reduce concerns about job displacement and build confidence in working alongside AI. In addition, SMEs should strengthen data governance and cybersecurity practices to manage the risks associated with increased digitalisation. Consistent with recent SLR evidence, AI strategies should be aligned with each firm's existing technological capabilities, resources, and readiness, with gradual digitalisation generally being more appropriate than large-scale, one-time transformation programmes. SMEs can further overcome limitations in technical expertise by engaging with universities, research laboratories, industry consortia, and government-supported digitalisation programmes. At the policy level, governments and regional development agencies should address structural resource constraints by establishing SME-focused AI innovation hubs, providing subsidised training and reskilling programmes, offering financial support for AI experimentation and adoption, and developing clear and accessible ethical and governance guidelines tailored to the needs and capabilities of smaller firms (Hossen et al., 2026).

LIMITATION AND FUTURE DIRECTION

A key limitation of the existing literature is its geographical imbalance, with more than 60% of empirical studies focusing on SMEs in Europe and East Asia, while developing economies in Africa, South Asia, and Latin America remain underrepresented. This limits the generalisability of findings because SMEs in developing contexts often face different levels of digital infrastructure, energy reliability, financial resources, technological skills, and regulatory support. Future research should therefore conduct comparative and cross-country studies across developed and emerging economies to examine how institutional, infrastructural, and socioeconomic conditions shape the relationship between AI adoption, SME performance, and environmental sustainability. Another important limitation is the dominance of cross-sectional research designs, which provide limited insight into the long-term environmental consequences of AI. Future studies should employ longitudinal approaches and lifecycle assessment to measure both the environmental costs of AI, including computing, data storage, and energy consumption, and its potential benefits through energy optimisation, resource efficiency, process automation, and reduced waste. Such approaches would provide stronger evidence of AI's actual net environmental impact over time.

In addition, the empirical literature on generative AI (GenAI) adoption among SMEs remains nascent, creating significant opportunities for future investigation. Research should examine how GenAI influences SME productivity, innovation, resource efficiency, and environmental performance, while also considering potential increases in computing and energy demand. Particular attention should be given to the governance challenges associated with GenAI, including data privacy, intellectual property, cybersecurity, algorithmic bias, misinformation, and accountability, especially because SMEs may lack the resources and expertise required to establish robust AI governance mechanisms. Future research could therefore adopt integrated and mixed-method approaches that combine quantitative longitudinal evidence with qualitative case studies to examine the economic, environmental, organisational, and governance implications of AI adoption. This would contribute to a more comprehensive understanding of when and under what conditions AI can support both SME competitiveness and long-term environmental sustainability.

CONCLUSION

Artificial intelligence serves as a powerful catalyst for sustainable digital transformation in SMEs, enabling improvements in operational efficiency, decision-making, automation, innovation, resource conservation, and social inclusion. However, these benefits are not automatic and cannot be achieved through technology acquisition alone. Realizing durable and responsible value requires the deliberate development of dynamic organizational capabilities, strategic leadership, managerial commitment, workforce empowerment, reliable data, and responsible governance, all aligned with Triple Bottom Line principles.

An integrated Resource-Based View–Dynamic Capabilities–Triple Bottom Line perspective helps explain how SMEs can convert AI resources into sustainable economic, environmental, and social outcomes. At the same time, barriers such as cost, skills shortages, infrastructure gaps, privacy and cybersecurity concerns, and limited organizational readiness often constrain progress. By addressing these challenges through phased and tailored implementation strategies, continuous workforce development, and supportive institutional policies, SMEs can harness AI to build resilient, inclusive, and environmentally responsible competitive futures.

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