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Digital Transformation, AI and Sustainability in Management and Economics

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Abstract: The convergence of digital transformation, artificial intelligence, and sustainability represents one of the most consequential paradigm shifts in contemporary management and economics. This paper develops an integrative synthesis of how digital technologies and AI reshape business models, organizational processes, and economic outcomes while simultaneously serving as critical enablers of environmental, social, and governance performance. Drawing on recent systematic reviews and empirical investigations, the paper (i) maps the conceptual linkages between digital transformation and the three pillars of sustainable development; (ii) analyses how AI deployment generates value across economic, environmental, and social dimensions; (iii) examines the distinctive challenges facing small and medium-sized enterprises in AI adoption; (iv) evaluates the role of machine learning in forecasting economic growth and multidimensional sustainability indicators; (v) discusses responsible AI governance and ethical leadership; and (vi) identifies theoretical and managerial implications. The analysis concludes that "twin transformation" — the synergistic combination of digital and sustainability transformation — emerges as a strategic imperative, but one that requires responsible governance, organizational change capacity, and inclusive stakeholder engagement to realize its full potential.

Keywords: digital transformation; artificial intelligence; sustainability; ESG performance; circular economy

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1. Introduction

Digital technologies and artificial intelligence have moved from operational back-office tools to strategic resources that redefine how firms create, deliver, and capture value (Enholm et al., 2021). Concurrently, sustainability has risen to the top of corporate agendas, driven by the United Nations Sustainable Development Goals, the European Green Deal, and mounting stakeholder pressure for environmental and social accountability. The intersection of these two trajectories — what scholars have labelled the digital imperative — is reshaping management theory and economic practice (Guandalini, 2022).

Despite a rapidly expanding body of literature, significant gaps remain. Research on the mutual relationship between digital transformation and sustainability has only recently been formalized at the firm level (Gómez-Trujillo & González-Pérez, 2021), the adoption of AI in sustainable business models remains under-theorized (Sipola et al., 2023), and empirical evidence on how machine learning can forecast sustainable development indicators is fragmented (Rabbi, 2025). This paper addresses these gaps by integrating insights across management, economics, ethics, and information systems into a unified conceptual synthesis.

The remainder of the paper is organized as follows. Section 2 establishes the theoretical and conceptual foundations. Sections 3–4 examine digital transformation and AI as drivers of sustainable business. Section 5 focuses on SMEs and AI adoption barriers. Section 6 reviews machine learning's role in economic and sustainability forecasting. Sections 7–8 cover responsible AI and organizational change. Section 9 discusses implications and Section 10 concludes with research directions.

2. Theoretical Foundations and Conceptual Framework

2.1 Digital transformation as a strategic phenomenon

Digital transformation refers to the comprehensive adoption and integration of digital technologies — such as AI, the Internet of Things, big data analytics, cloud computing, and blockchain — into business processes, organizational structures, and value-creation logics. From a Resource-Based View, these technologies constitute strategic resources that, when combined with complementary organizational capabilities, generate sustained competitive advantage (Khan et al., 2024). Recent literature positions digitalization as an operant rather than merely operand resource, capable of reconfiguring entire business ecosystems (Guandalini, 2022).

A systematic literature review across 75 studies identified digital transformation as both a driver and a predecessor of corporate sustainability, suggesting a recursive reinforcement loop rather than a unidirectional causal chain (Gómez-Trujillo & González-Pérez, 2021). Five interconnected mechanisms were later synthesized in the Digital-Sustainability Ecosystem framework: efficiency gains, dematerialization, circular economy enablement, innovation acceleration, and digital collaboration (Florek-Paszkowska & Ujwary-Gil, 2025). Each of these mechanisms simultaneously captures value and advances sustainability objectives, although tensions persist — particularly regarding the energy demands of large-scale AI training.

2.2 Twin transformation: digital + sustainability

The concept of Twin Transformation captures the deliberate integration of digital and sustainability strategies. Rather than treating them as parallel workstreams, Twin Transformation posits that data streams, predictive analytics, and generative AI capabilities can overcome the cognitive boundaries limiting human rationality in addressing complex sustainability problems (Crome et al., 2024). In this view, digitalization provides the means while sustainability provides the ends, and AI acts as the integrative translator between them.

2.3 AI as a general-purpose technology for sustainability

Following Sipola, Saunila, and Ukko's qualitative study of 25 of the largest Finnish enterprises during 2017–2021, AI can be conceptualized as a generalizing technology whose strategic significance is steadily increasing (Sipola et al., 2023). Their analysis revealed that AI deployment was driven by two interlinked aims: optimization of internal processes, and the pursuit of benefits in multiple dimensions of sustainable business (Sipola et al., 2023). Sixteen of the twenty enterprises that adopted AI explicitly linked the technology to sustainability outcomes, providing early empirical evidence that the relationship is not merely assumed but operationally pursued.

3. Digital Transformation and Corporate Sustainability

3.1 Three-dimensional impact: environment, social, governance

A systematic bibliometric literature review of the digital transition and sustainability concluded that AI, big data analytics, IoT, and mobile technologies are particularly impactful in environmental domains, including sustainable urban development, sustainable production, and pollution control (Rosário & Dias, 2022). In economic terms, emerging digital technologies drive transformation toward a circular economy, digital sharing economy, and sustainable manufacturing (Rosário & Dias, 2022). For social sustainability, however, the review identified a critical asymmetry: technology deployment can exacerbate the digital divide, requiring multidimensional policy perspectives to ensure inclusive outcomes (Rosário & Dias, 2022).

3.2 ESG performance and total factor productivity

Empirical evidence from Chinese listed firms during 2010–2019 establishes a robust positive relationship between digital transformation and corporate ESG performance (Yang et al., 2023). Using panel data and fixed-effects estimation, this study identified three mediating mechanisms: digital transformation promotes corporate green innovation, improves information transparency, and enhances corporate governance — all of which reinforce ESG outcomes (Yang et al., 2023). The effect is particularly salient for high-tech firms and state-owned enterprises, and is moderated by government subsidies and the career experience of chief executive officers (Yang et al., 2023).

Ding et al. extend this work by demonstrating that digital transformation boosts corporate total factor productivity, with ESG performance functioning as a partial mediator: social performance plays a mediating effect while environmental performance serves as a suppressing effect (Ding et al., 2024). Their central finding is that the primary driver of TFP improvement is the direct effect of digital transformation, rather than the indirect pathway through ESG factors,

suggesting that managers should pursue digital transformation as an integral productivity strategy and not relegate it to a sustainability side-project (Ding et al., 2024).

Further large-sample evidence confirms the positive impact of digital transformation on corporate performance, with ESG practices strengthening this relationship through asymmetric information reduction (Bo & Li, 2025). Across 4,922 Chinese listed firms from 2010 to 2022, robust ESG implementation multiplied the performance gains generated by digital transformation investments (Bo & Li, 2025).

Chen, Ren, and Shu identify six transmission channels through which corporate digital translation enhances ESG performance: energy saving discouragement of greenwashing behavior improvement of technological innovation improvement of social responsibility alleviation of information asymmetry, and enhancement of risk management (Chen et al., 2025). Importantly, this relationship intensifies under conditions of market competition but weakens in the presence of cyberattacks — underscoring that digitalization is a double-edged tool whose sustainability benefits are conditional on cybersecurity readiness (Chen et al., 2025).

3.3 Financing constraints as a boundary condition

Yang and Han's panel study of 710 listed Chinese corporates from 2011 to 2020 reveals that financing constraints are a critical boundary condition (Yang & Han, 2023). When FCs are loose, digital transformation's impact on ESG performance — particularly environmental and social — is more visible. Among corporates with low FCs, private firms, and non-technical firms, easing financing constraints amplifies the ESG gains from digitalization (Yang & Han, 2023). This implies that capital-market frictions can blunt the sustainability dividend of digital transformation, calling for coordinated industrial and financial policy interventions.

4. AI in Sustainable Business: Value Creation and Business Model Innovation

4.1 AI and business value

The literature on AI and business value has rapidly matured. Enholm, Papagiannidis, Mikalef, and others reviewed how AI capabilities create business value across process optimization, customer experience, and sustainability dimensions (Enholm et al., 2021). Their synthesis shows that AI-driven personalized services can reduce customer attrition, but also that AI-powered chatbots can yield frustration and dissatisfaction when poorly designed — illustrating that value capture is conditional on user-centered design (Enholm et al., 2021). From a sustainability perspective, the same review positions AI as a disruptive potential that can drive business model innovation toward sustainable development (Enholm et al., 2021).

Perifanis and Kitsios conducted a comprehensive review of 139 peer-reviewed articles using Webster and Watson's methodology, concluding that despite the revolutionary potential of AI capabilities, the resource orchestration and governance required for strategic AI implementation remain complex and conceptually under-developed (Perifanis & Kitsios, 2023). Their framework highlights that organizations will succeed in the digital transformation era only by precisely adopting and implementing these emerging technologies, while integrating them with business and IT strategies (Perifanis & Kitsios, 2023).

4.2 AI, process optimization, and sustainability performance

Khan, Mehmood, and Ali's RBV-anchored empirical study of 288 organizations demonstrates positive relationships between AI adoption and process optimization, and between AI adoption and sustainability performance (Khan et al., 2024). Process optimization functions as a mediator, and organizational flexibility as a moderator, of the AI-sustainability link (Khan et al., 2024). Indirect effects of AI on sustainability via process optimization are confirmed under the boundary conditions of organizational flexibility (Khan et al., 2024). These findings reinforce the strategic narrative of AI as a resource that simultaneously improves operational effectiveness and environmental responsibility, particularly for practitioners leveraging AI driven by organizational capabilities (Khan et al., 2024).

4.3 AI-enabled Twin Transformation

Crome, Graf-Drasch, Oberländer, and colleagues provide a framework for AI-enabled Twin Transformation that emphasizes the predictive and generative capabilities of data-driven systems (Crome et al., 2024). Such systems, they argue, can overcome human cognitive limits in navigating the complex problem space at the intersection of digital and sustainability transformation (Crome et al., 2024). The framework calls for a joint discourse that explicitly coordinates digital and sustainability strategies, rather than treating them as separate governance domains (Crome et al., 2024).

4.4 Smart learning systems and sustained competitive advantage

Emerging research positions AI-enabled smart learning systems as pathways to sustainable growth. Khan's qualitative review argues that AI enhances decision-making accuracy, operational efficiency, and adaptive learning capabilities, enabling organizations to align innovation with sustainability goals (Khan, 2026). The conclusion is that sustainable growth in the digital era requires not only smart technologies but also continuous learning ecosystems that embed ethical, environmental, and strategic intelligence into business operations (Khan, 2026).

5. AI Adoption in SMEs: Drivers, Barriers, and Frameworks

5.1 The SME lag and its causes

Small and medium-sized enterprises lag large corporations in AI adoption, despite their centrality to most economies. Proietti and Magnani identify a significant gap between SMEs and large corporations in the use of AI, with SMEs facing numerous barriers to adoption (Proietti & Magnani, 2025). This gap is consequential because SMEs face vastly different starting conditions, including data availability, infrastructure maturity, and managerial capabilities (Oldemeyer et al., 2024).

A systematic literature review based on the PRISMA protocol identified 27 distinct challenges perceived by SMEs in adopting AI, with the most cited barriers being: lack of knowledge, costs, and inadequate infrastructure (Oldemeyer et al., 2024). Across studies, knowledge is mentioned "much more often than all other" barriers, costs rank second, and the maturity level of the SME itself ranks third (Proietti & Magnani, 2025). Perceived ease of use and perceived advantages further mediate adoption decisions, in line with technology acceptance models (Proietti & Magnani, 2025).

5.2 Four primary barriers and practical insights

Závodná, Überwimmer, and Frankus synthesize findings into four primary barriers: lack of trust, lack of knowledge, lack of infrastructure, and lack of resources (Závodná et al., 2024). Pilot research indicates that despite the high costs associated with AI, funding was not always the top concern; SMEs often prioritized practical support, such as access to technical expertise and real-world examples, over pure financial subsidies (Závodná et al., 2024). This suggests that practical support mechanisms should accompany funding programs to maximize adoption rates (Závodná et al., 2024).

Data quality and inadequate data management practices can also hinder effective AI implementation, and SMEs frequently struggle to scale AI solutions beyond initial pilots (Závodná et al., 2024). Resistance from employees accustomed to traditional practices further slows adoption, requiring deliberate change-management interventions (Závodná et al., 2024).

5.3 A framework for SME AI implementation

Iyelolu, Agu, Idemudia, and colleagues outline a comprehensive strategy. They document that AI technologies can significantly enhance operational efficiency, product development, customer engagement, and competitive advantage for SMEs (Iyelolu et al., 2024). Key enabling strategies include government incentives, public–private partnerships, affordable AI-as-a-Service models, and targeted training programs to build AI competencies within SMEs (Iyelolu et al., 2024). The establishment of a supportive ecosystem with robust infrastructure, favorable regulatory frameworks, and access to funding is essential (Iyelolu et al., 2024). Proietti and Magnani extend this with an implementation framework proposing actionable guidelines for SMEs to overcome adoption challenges (Proietti & Magnani, 2025).

6. Machine Learning for Economic and Sustainability Forecasting

6.1 Machine learning for sustainable development indicators

Machine learning increasingly supports evidence-based sustainability policy. A recent study of the European Union uses Random Forest regression for feature selection, Long Short-Term Memory networks for temporal forecasting, SHapley Additive exPlanations for interpretability, and the Technique for Order of Preference by Similarity to Ideal Solution for multi-criteria decision analysis across seven EU countries from 2014 to 2023 (Rabbi, 2025). The framework identifies three principal drivers of integrated sustainability: Global Value Chain Backward Participation, Social Protection Expenditure, and Municipal Recycling Rate (Rabbi, 2025).

Critically, this study articulates policy thresholds: FDI below €327 million balances economic gains and environmental costs; social protection spending above 25.6% of GDP reduces workplace fatalities when the gender pay gap remains under 21.3%; and a 10% increase in recycling rates correlates with a 2.3 tonnes per capita reduction in CO_2 emissions

(Rabbi, 2025). LSTM projections forecast GDP stabilization at 2%–3% by 2030, but warn of resource productivity declines in Southern Europe without targeted intervention (Rabbi, 2025).

6.2 XGBoost for sustainable development

Knio and Balikel demonstrate the use of XGBoost to predict sustainable development indicators — GDP, employment, and CO_2 emissions — using annual panel data for Brazil, Canada, China, and India from 2005 to 2023 (Knio & Balikel, 2025). Their findings indicate high accuracy for GDP forecasting, with balance of payments, climate policy, and green investment emerging as important predictors (Knio & Balikel, 2025). CO_2 and employment forecasts were less accurate because they were overfitted, pointing to the need for higher-frequency data and hybrid models in future work (Knio & Balikel, 2025).

6.3 Unsupervised learning for the Harmonic Development Index

Bakk, Simon, and György apply Self-Organizing Maps and Bayesian networks to the Harmonic Development Index (H2DI) — an integrative composite indicator covering economic, financial, environmental, social, demographic, and knowledge-based dimensions (Bakk et al., 2026). Their approach captures nonlinearities and probabilistic dependencies that PCA and k-means methods cannot, demonstrating that robust economic and financial sustainability correlate positively with social resilience and knowledge capacity but inversely with demographic vitality (Bakk et al., 2026). Cross-temporal robustness checks from 2005 to 2023 affirm that these relationships remain stable despite global shocks (Bakk et al., 2026).

6.4 ML and economic growth

Hu's review of ML applications in economic forecasting covers supervised learning — regression trees, support vector machines, ensemble methods (random forests, gradient boosting) — and deep learning approaches including neural networks (Hu, 2025). The review identifies persistent challenges related to data quality, model interpretability, overfitting, and ethical considerations, arguing that transparency and accountability in ML development are prerequisites for bias-free and policy-relevant forecasting (Hu, 2025).

Shaker et al. extend this conversation to Sustainable Development Goal 8, emphasizing that ML can support job creation, workplace safety, and economic expansion — provided that technological advancement is balanced with labor rights and social protections (Shaker et al., 2024). Their systematic review highlights the necessity of striking a balance between technological progress and equitable outcomes (Shaker et al., 2024).

7. Responsible AI and Ethical Governance

7.1 Dimensions of AI governance

Camilleri identifies key dimensions of AI governance drawn from frameworks proposed by technology conglomerates, policymakers, and intergovernmental organizations: the promotion of accountability and transparency; explainability, interpretability, and reproducibility; fairness and inclusiveness; privacy and safety of end users; and the prevention of risks and cyber-security issues (Camilleri, 2023). All those involved in research, development, and maintenance of AI systems bear social and ethical responsibilities toward consumers and society (Camilleri, 2023).

7.2 Algor-ethics and global regulatory diversity

Ricciardi Celsi and Zomaya examine the concept of algor-ethics — a framework for embedding ethical considerations throughout the AI lifecycle — as an antidote to algocracy, where power becomes concentrated in those who control data and algorithms (Celsi & Zomaya, 2025). Comparing six major jurisdictions (the United States, China, the European Union, Japan, Canada, and Brazil), they highlight that the EU's AI Act and Japan's and Canada's frameworks prioritize fundamental rights and risk-based regulation, the US favors innovation with executive directives and sector-specific oversight, China's framework integrates AI governance with state-driven socialist core values, and Brazil's framework remains institutionally shallow despite rhetorical commitment to fairness and democratic oversight (Celsi & Zomaya, 2025).

7.3 Responsible AI Integration Models

Akhtar, Mittal, and Rahman propose the Responsible AI Integration Model, demonstrating that responsible AI reduces algorithmic bias and reputational risk while enhancing innovation, employee engagement, and stakeholder confidence

(Akhtar et al., 2026). Their Responsible AI framework improves ethical governance systems, explainability procedures, and inclusive designs — improving both operational efficiency and ethical standing simultaneously (Akhtar et al., 2026).

7.4 Ethical leadership and transparency

Jundon et al. argue that ethical leadership is critical in maintaining trust during digital transformation: leaders must ensure responsible technology use, data privacy, and fairness in AI decisions (Jundon et al., 2025). Critical ethical issues include bias in AI algorithms, transparency gaps, extensive data collection raising privacy concerns, and automation's disruption of labor markets (Jundon et al., 2025). Effective management requires fairness-aware algorithms, robust data security, proactive workforce transition strategies, and adherence to global standards (Jundon et al., 2025).

Kaur reinforces that responsible AI governance should go beyond legal compliance, integrating ethical practices that improve transparency, accountability, and fairness (Kaur, 2024). These practices are essential both for avoiding harm and for restoring public trust in AI-enabled business processes (Kaur, 2024).

8. Organizational Change Management for Digital Adoption

8.1 The human and cultural dimension

Digital transformation extends well beyond technology adoption. Madanchian and Taherdoost argue that successful implementation requires strategic and mindset shifts; employees must understand the influence of digital technologies and accept change, while leaders must facilitate transitions across the organization (Madanchian & Taherdoost, 2022). Organizational change is therefore one of the most critical success factors, and resistance to change alongside lack of support is one of the main reasons for digital transformation failure (Madanchian & Taherdoost, 2022).

Purnamasari et al. confirm that digital transformation brings fundamental changes in operational aspects, requiring adjustments not only in technology but also in work culture, organizational structure, and human resource mindsets (Purnamasari et al., 2025). Robust change management enables organizations to increase effectiveness and innovation, ensuring survival in global competition (Purnamasari et al., 2025).

8.2 Critical success factors and best practices

Ibrahim, Okafor, Wedraogo, and colleagues conducted a systematic literature review of 38 peer-reviewed articles and industry reports published between 2020 and 2025 (Ibrahim et al., 2025). Thematic analysis identifies visionary leadership, strong stakeholder engagement, organizational culture alignment, and continuous communication as central to effective change (Ibrahim et al., 2025). Resistance is a recurrent challenge, driven by fear of the unknown, lack of training, and organizational inertia (Ibrahim et al., 2025). The study concludes that embedding change management as a core component of digital transformation significantly enhances the likelihood of sustainable outcomes (Ibrahim et al., 2025).

Bhattarai's statistical analysis of 100 participants across diverse enterprises confirms that change-management strategies have measurable impact on organizational performance, identifying the most effective strategies through empirical investigation (Bhattarai, 2025).

8.3 OCM strategies for sustained adoption

Dhiman lists the critical components: development of resilient strategies, employee engagement, skill development, and management of resistance (Dhiman, 2025). He emphasizes the integration of automation and AI for process optimization and the use of performance dashboards to monitor and evaluate digital adoption (Dhiman, 2025). The chapter provides actionable insights for leaders, offering a strategic framework to foster a culture of continuous adaptation and improvement in the digital age (Dhiman, 2025).

9. Circular Economy and Digital Business Models

9.1 Digital technologies as catalysts

Ranta, Aarikka-Stenroos, and Väisänen show that digital technologies can catalyze business model innovation for the circular economy, as multiple case studies demonstrate (Ranta et al., 2020). Neligan et al. provide empirical substantiation: in a survey of 895 German firms (599 manufacturers and 296 industrial service providers), companies with a strong digital focus are more likely to adopt circular business models (Neligan et al., 2022). Digitalization's role in driving disruptive innovations, new business models, and novel forms of collaboration can accelerate the transition to resource-efficient and circular production systems (Neligan et al., 2022).

9.2 Industrial digitalization and BMI

Parida, Sjödin, and Reim's review identifies that digitalization is revolutionizing industrial value chains through IoT, intensive data exchange, and predictive analytics, but profiting from these technologies requires business model innovation (Parida et al., 2019). Their framework links digitalization, BMI, and sustainability in industrial settings, addressing value creation, value delivery, and value capture — and showing that alignment across these components is required to drive sustainable industry initiatives (Parida et al., 2019).

Agrawal et al. document that digitalization has a positive impact on business models for sustainable manufacturing, but also note inverse relationships between environmental and economic advantages under certain configurations — a finding that should temper enthusiasm with rigorous design of CE business models (Agrawal et al., 2021).

Oghazi, Mostaghel, and Hultman extend this to international industrial manufacturers, revealing the characteristics of digitally enabled circular business models and their outcomes in resource utilization, supply chain transformation, and sustainable efficiency (Oghazi et al., 2024). Their case study emphasizes the role of master firms in orchestrating partners and sister companies toward circular outcomes (Oghazi et al., 2024).

10. Implications

10.1 Theoretical implications

The integrated literature points to several theoretical implications. First, the relationship between digital transformation and sustainability is recursive: digital investment strengthens ESG performance, which in turn reinforces total factor productivity and long-run value creation (Ding et al., 2024; Yang et al., 2023). This challenges simple linear models that subordinate sustainability to economic performance, suggesting instead a virtuous cycle in which digital capabilities, sustainability practices, and productivity reinforce each other.

Second, AI should not be treated as a stand-alone technology but as a generalizing capability that integrates with organizational slack, process optimization, and flexibility to produce sustainability outcomes (Khan et al., 2024; Sipola et al., 2023). Pure technology deployment without complementary organizational capabilities produces underwhelming results — a finding consistent with RBV predictions about resource bundling.

Third, the boundary conditions — financing constraints, cybersecurity readiness, market competition, organizational culture — are decisive in determining whether digital transformation translates into ESG gains (Chen et al., 2025; Yang & Han, 2023). Theoretical models must therefore incorporate contextual moderators to be useful for prescriptive purposes.

Fourth, the emerging Twin Transformation paradigm offers a unifying lens for thinking about how digital and sustainability strategies can be deliberately co-designed, rather than pursued as parallel workstreams (Crome et al., 2024). The Digital-Sustainability Ecosystem framework synthesizes five mechanisms — efficiency gains, dematerialization, circular economy enablement, innovation acceleration, and digital collaboration — that map the theoretical pathways (Florek-Paszkowska & Ujwary-Gil, 2025).

10.2 Managerial implications

For practitioners, several imperatives emerge. First, ESG practices should be embedded within — not appended to — digital transformation programs, because ESG effectiveness amplifies digital transformation's impact on corporate performance (Bo & Li, 2025). Second, AI deployment should be staged, with explicit attention to process optimization as a mediating mechanism and organizational flexibility as a moderating condition (Khan et al., 2024). Third, SMEs should prioritize practical support — including access to technical expertise, real-world examples, and AI-as-a-Service models — alongside traditional financial subsidies (Iyelolu et al., 2024; Závodná et al., 2024). Fourth, change management should be embedded as a core component of digital transformation programs from inception, with continuous communication, stakeholder engagement, and leadership visioning (Ibrahim et al., 2025). Fifth, responsible AI governance must accompany deployment — via fairness-aware algorithms, transparency mechanisms, data privacy protections, and proactive workforce transition planning (Akhtar et al., 2026; Jundon et al., 2025; Kaur, 2024).

10.3 Policy implications

For policymakers, the integrated findings suggest three priorities. (i) Coordinate industrial and financial policies so that digital transformation investments are not blunted by financing constraints (Yang & Han, 2023). (ii) Invest in cyberse-

curity and trust infrastructure, without which the ESG gains from digital adoption weaken (Chen et al., 2025). (iii) Provide practical, hands-on support to SMEs — through partnerships, plain-language guidance, and AI-as-a-Service ecosystems — to complement financial incentives (Iyelolu et al., 2024; Závodná et al., 2024).

11. Conclusion and Future Research

Digital transformation, AI, and sustainability jointly constitute one of the defining paradigm shifts of contemporary management and economics. The evidence synthesized in this paper demonstrates that:

Digital transformation positively influences corporate ESG performance, with multiple mediating mechanisms (Gómez-Trujillo & González-Pérez, 2021; Yang et al., 2023).

AI functions as a generalizing technology that, when bundled with process optimization and organizational flexibility, produces measurable sustainability gains (Khan et al., 2024; Sipola et al., 2023).

SMEs face distinctive adoption barriers — knowledge gaps, costs, infrastructure, maturity — and benefit most from practical, expertise-based support alongside financing (Oldemeyer et al., 2024; Proietti & Magnani, 2025; Závodná et al., 2024).

Machine learning — including LSTM, XGBoost, Random Forest, and Self-Organizing Maps — increasingly offers evidence-based forecasting of multidimensional sustainability indicators, with policy-actionable thresholds (Bakk et al., 2026; Knio & Balikel, 2025; Rabbi, 2025).

Responsible AI governance, ethical leadership, and regulatory frameworks are necessary to ensure that digitalization produces inclusive and trustworthy outcomes (Akhtar et al., 2026; Camilleri, 2023; Celsi & Zomaya, 2025; Jundon et al., 2025).

Twin Transformation, integrating digital and sustainability strategies, emerges as the strategic horizon (Crome et al., 2024; Florek-Paszkowska & Ujwary-Gil, 2025).

Future research should focus on several open questions. First, longitudinal case studies across diverse industries and geographies are needed to validate the Twin Transformation framework at sectoral scale. Second, the dark side of AI-enabled sustainability — including rebound effects, hidden energy costs, and algorithmic bias — warrants deeper empirical investigation. Third, cross-sectoral collaborations between large firms and SMEs in circular business models require new governance archetypes. Fourth, the joint discourse on responsible AI must evolve to produce globally interoperable standards while preserving regional flexibility. Fifth, the application of advanced AI techniques — including generative models and reinforcement learning — to economic and sustainability forecasting remains nascent. Finally, scalable frameworks for AI implementation in SMEs, tailored to their unique constraints and opportunities, represent an urgent research priority (Iyelolu et al., 2024; Proietti & Magnani, 2025).

The pivotal insight from this synthesis is that digital transformation is neither a sufficient nor a complete answer to sustainability challenges. When intentionally coupled with responsible AI, robust ESG practices, organizational change capacity, and inclusive stakeholder governance, however, it constitutes a transformative force for systemic sustainability improvement in both management and economics.

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