Manara
Qatar Research Repository
by Qatar National Library

Digital levers for sustainability: a meta-analytic review of digital transformation's influence on ESG performance

Dedrix Stephenson Bindeeba, Eddy Kurobuza Tukamushaba, Rennie Bakashaba

Item type
Journal Contribution

Terms of use
This work is licensed under a CC BY 4.0 license

This version is available at
https://manara.qnl.qa/articles/journal_contribution/Digital_levers_for_sustainability_a_meta-analytic_review_of_digital_transformation_s_influence_on_ESG_performance/30219091/1
Access the item on Manara for more information about usage details and recommended citation.

Posted on Manara – Qatar Research Repository on
2025-09-29

Cogent Business & Management

ISSN: 2331-1975 (Online) Journal homepage: www.tandfonline.com/journals/oabm20

Digital levers for sustainability: a meta-analytic review of digital transformation's influence on ESG performance

Dedrix Stephenson Bindeeba, Eddy Kurobuza Tukamushaba & Rennie Bakashaba

To cite this article: Dedrix Stephenson Bindeeba, Eddy Kurobuza Tukamushaba & Rennie Bakashaba (2025) Digital levers for sustainability: a meta-analytic review of digital transformation's influence on ESG performance, Cogent Business & Management, 12:1, 2564919, DOI: 10.1080/23311975.2025.2564919

To link to this article: https://doi.org/10.1080/23311975.2025.2564919

© 2025 The Author(s). Published by Informa UK Limited, trading as Taylor & Francis Group

View supplementary material

Published online: 26 Sep 2025.

Submit your article to this journal

View related articles

View Crossmark data

Full Terms & Conditions of access and use can be found at
https://www.tandfonline.com/action/journalInformation?journalCode=oabm20

COGENT BUSINESS & MANAGEMENT
2025, VOL. 12, NO. 1, 2564919
https://doi.org/10.1080/23311975.2025.2564919

OPERATIONS MANAGEMENT | REVIEW ARTICLE

OPEN ACCESS Check for updates

Digital levers for sustainability: a meta-analytic review of digital transformation's influence on ESG performance

Dedrix Stephenson Bindeeba[a], Eddy Kurobuza Tukamushaba[b] and Rennie Bakashaba[a]

[a]Faculty of Business and Management Sciences, Mbarara University of Science and Technology, Mbarara, Uganda; [b]College of Business, University of Doha for Science and Technology, Doha, Qatar

ABSTRACT

Digital transformation (DT) is reshaping how firms meet environmental, social, and governance (ESG) expectations. This meta-analysis pools 59 studies (2015–2025) covering 835,000 firm-year observations to quantify DT's ESG impact. Anchored in Resource-Based View, Stakeholder, and Dynamic Capabilities theories, the effects of ESG pillar and DT typologies are separated. DT raises ESG scores; among technologies, business-process digitization delivers the largest gains, followed by data-infrastructure upgrades, while AI adds value only where ethics and oversight are mature. Environmental metrics improve most consistently; social and governance benefits appear but hinge on firm capabilities and regulatory context. Subgroup and meta-regression tests show stronger DT–ESG links in manufacturing and service sectors and in post-2022 samples, suggesting curves and tightening standards. Results guide managers to sequence investments process first, analytics later and urge policymakers to link incentives to verifiable digital disclosures. Future work should extend evidence to under-studied regions and next-wave tools such as blockchain and digital twins.

ARTICLE HISTORY
Received 29 May 2025
Revised 3 September 2025
Accepted 17 September 2025

KEYWORDS
Digital transformation; ESG performance; sustainability; Meta-Analysis; corporate governance

SUBJECTS
Sustainable Development; Environmental Economics; Environment & the Developing World

1. Introduction

In today's global economy, firms carry a double load: outperform rivals while proving they are responsible corporate citizens. Climate change is accelerating, income gaps are widening, and governance failures keep filling news cycles, so investors, regulators, and the public now watch environmental, social, and governance (ESG) metrics almost as closely as earnings (OECD, 2024; Crona et al., 2021). The 2015 Paris Agreement pushed this shift from rhetoric to disclosure. Since then, standards setters and civil-society groups have demanded clearer ESG reporting, deeper assurance, and tangible accountability (UNFCCC, 2015; Robeco, 2023). At the same time, a wave of digital innovation, artificial intelligence (AI), big-data analytics, the Internet of Things (IoT), and cloud computing has changed how organizations collect information, make decisions, and engage stakeholders. These tools do more than raise productivity; they create live dashboards, auditable trails, and predictive insights that can expose ESG risks in real time (Li et al., 2024b; Wang & Wang, 2025).

Digital transformation (DT) is the deliberate integration of such technologies into business models and processes to boost efficiency, flexibility, and value (Ding et al., 2024; Lu et al., 2024). ESG performance, by contrast, is a scorecard of real achievements, lower emissions, safer workplaces, ethical supply chains, and transparent oversight (Chen & Wang, 2024; Zheng & Bu, 2024). Both constructs are multi-layered. DT spans intelligent platforms such as AI, process-oriented systems like enterprise-resource-planning suites, and foundation services, including cloud infrastructure. ESG encompasses three intertwined pillars, environmental, social, and governance, each with several sub-dimensions (Su et al., 2023; Zheng & Bu, 2024). Research on the intersection of these agendas is

CONTACT Dedrix Stephenson Bindeeba dedrixbindeeba@gmail.com Faculty of Business and Management Sciences, Mbarara University of Science and Technology, P.O. Box 24985, Kampala, Uganda

Supplemental data for this article can be accessed online at https://doi.org/10.1080/23311975.2025.2564919.

© 2025 The Author(s). Published by Informa UK Limited, trading as Taylor & Francis Group
This is an Open Access article distributed under the terms of the Creative Commons Attribution License (http://creativecommons.org/licenses/by/4.0/), which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited. The terms on which this article has been published allow the posting of the Accepted Manuscript in a repository by the author(s) or with their consent.

growing fast, with scholars asking whether specific digital applications can move the needle on each ESG pillar.

Several mechanisms suggest they can. AI and big-data analytics improve environmental forecasting, enable continuous emissions monitoring, and sharpen predictive risk management (Celestin 2024; Wang & Wang, 2025). IoT sensors cut energy waste and trace resources along sprawling supply chains (Ren & Mohd Isa, 2023). Digital reporting platforms and blockchain ledgers tighten internal controls and make governance processes more transparent (Xie et al., 2024; Zhang, 2024). Three well-established theories frame these pathways. The Resource-Based View (RBV) argues that digital assets create advantage only when they are valuable, rare, inimitable, and non-substitutable (Barney, 1991; Cui, 2025). Stakeholder Theory holds that traceability and open data build legitimacy with customers, investors, and regulators (Freeman, 1984; Luo, 2024). Dynamic Capabilities Theory (DCT) stresses that firms must constantly reconfigure resources and routines to seize emerging sustainability opportunities (Sang et al., 2024; Teece et al., 1997).

Yet empirical results are anything but uniform. Some studies report strong positive links between DT and ESG, especially when digital investment fuels green innovation, supports evidence-based decisions, or enhances disclosure quality (Ding et al., 2024; Wu, 2024). Others find weak or even negative effects. Ren and Mohd Isa (2023) show that environmental benefits materialize only indirectly through innovation outcomes rather than from digital spending alone. Wang and Hou (2024) document a negative direct effect, citing implementation costs and poor organizational alignment. Context matters as well. Celestin (2024) observes notable ESG gains from AI in Ghanaian finance and manufacturing, whereas Liu et al. (2025) see negligible or adverse social impacts among Chinese multinationals. These inconsistencies point to a complex interaction among technology type, ESG pillar, firm capabilities, and institutional setting.

Prior reviews have added pieces to the puzzle, but leave critical questions open. Mendonça et al. (2025) highlight conceptual and methodological challenges in ESG research, yet overlook digital triggers. Tan et al. (2025) map the ESG–digitalization landscape bibliometrically but admit they do not integrate empirical findings or separate pillar-level effects. Bindeeba et al. (2025c) offer a meta-analysis of DT and sustainability but merge the three ESG pillars into a single index, hiding domain-specific patterns. Kalyani and Mondal (2024) analyze ESG, performance links without treating DT as a driver. Three recurrent problems emerge: DT is often handled as a monolith, ESG pillars are bundled, and contextual moderators receive uneven attention (Sang et al., 2024; Zhao et al., 2025). Without a targeted synthesis that disaggregates technologies, pillars, and contexts, theory development and managerial guidance both stall.

These gaps are tackled based on a comprehensive meta-analysis of 59 peer-reviewed studies, representing 835,000 firm-year observations across industries, regions, and digital technologies. Meta-analysis reconciles conflicting evidence by aggregating effect sizes and testing heterogeneity in a transparent, quantitative way. Unlike narrative or conceptual reviews, it produces quantitative insights while remaining transparent and reproducible. The inquiry addresses three challenges. First, unpacking DT into intelligent platforms, process digitalization, and foundational infrastructure to identify which category drives which ESG outcome. Second, treating ESG as separate environmental, social, and governance pillars, probing where digital investment pays off most. Third, key moderators are tested; geography, regulatory regime, ownership structure, and firm size, to reveal the conditions that strengthen or weaken DT's impact.

This study addresses five research questions: (i) What is the overall effect of digital transformation on ESG performance? (ii) Which ESG dimension, environmental, social, or governance, is most strongly influenced by DT? (iii) Which types of DT tools are most effective for specific ESG outcomes? (iv) Under what organizational and institutional conditions do DT–ESG relationships vary? (v) How have these relationships evolved over time and across global regions?

Following PRISMA 2020 guidelines, a random-effects model complemented by subgroup comparisons and meta-regressions was applied. Grounded in RBV, Stakeholder Theory, and DCT, this study makes four contributions. First, it offers the most extensive quantitative synthesis of DT's influence on ESG to date, covering a broad array of technologies, sectors, and regions. Second, it pinpoints which digital strategies deliver the greatest environmental, social, and governance gains, giving executives a clearer playbook. Third, it uncovers firm-level and external moderators, helping scholars refine theories about when and why DT works. Fourth, it charts how DT–ESG effects have evolved over the past decade and vary geographically, informing policymakers who aim to leverage digital tools for sustainable development.

The remainder of the paper is organized as follows. Section 2 reviews the literature on digital transformation and ESG. Section 3 outlines our meta-analytic methodology. Section 4 presents the aggregated results. Section 5 discusses theoretical and managerial implications. Section 6 concludes with directions for future research.

2. Literature review

2.1. Digital transformation typology

DT has evolved from a tool for operational efficiency into a strategic lever for sustainable business value. Drawing on Asbeetah et al. (2025) and Kwilinski et al. (2023), DT is defined as the integration of digital technologies to enable strategic renewal. Empirical studies vary in how DT is operationalized, often masking the nuanced effects of distinct technologies. To clarify these effects, DT is categorized into five typologies: (i) General DT maturity (e.g. digital orientation, IT investment intensity) (Pham et al., 2024), (ii) AI and intelligent systems (e.g. predictive analytics, robotics) (Al Halbusi et al., 2025), (iii) Data and Infrastructure (e.g. big data platforms, cloud systems), (iv) Business Process Digitization (e.g. ERP, workflow automation) (Wang & Zhang, 2024), and (v) Innovation Capabilities (e.g. smart product development, digital R&D) (Khan et al., 2023). These typologies align with firm capabilities that influence ESG outcomes differently. For example, AI tools enhance monitoring but pose governance risks (Li & Li, 2025), while ERP systems support compliance automation (Chen & Ren, 2025). Disaggregating DT helps explain divergent ESG impacts and underlines the need for meta-analytic synthesis.

2.2. ESG performance dimensions

ESG performance refers to a firm's ability to generate long-term value while meeting environmental, social, and governance expectations. These three pillars are often assessed using composite scores, yet empirical evidence shows uneven digital impact across each (Li et al., 2025; Pursiainen et al., 2021; Wang et al., 2023). Environmental performance includes carbon reduction and energy efficiency, often enabled by AI and IoT systems (Bindeeba et al., 2025b; Zhu & Jin, 2023). Social performance involves workforce safety, diversity, and stakeholder engagement, with evidence showing mixed outcomes, especially in developing economies, due to digital inequalities (Afum et al., 2024; Bindeeba et al., 2025c). Governance performance, while critical, is often under-theorized. Tools like blockchain and digital compliance systems strengthen audit quality but may reduce oversight if not well managed (Xie & Wu, 2025). Prior studies inconsistently theorize these effects and tend to privilege Global North contexts, leaving gaps in Africa and Southeast Asia (Ren & Mohd Isa, 2023). This fragmented evidence highlights the value of a typology-based synthesis to understand how digital transformation interacts with each ESG pillar.

2.2.1. Environmental performance

Environmental performance captures a firm's response to climate risk and resource use. Typical indicators include greenhouse gas emissions, energy efficiency, and pollution control (Raza & Woxenius, 2023; Yusof et al., 2020). Digital technologies play a key role in monitoring, forecasting, and mitigation. For instance, AI and IoT are used for real-time emissions tracking, smart metering, and supply chain traceability (Qaiser et al., 2025; Zhao et al., 2025). In China, predictive analytics have enabled firms to anticipate environmental penalties (Y. Wang & Wang, 2025), while in Ghana, mobile-based monitoring improved emissions accountability (Celestin, 2024). However, these outcomes are often mediated by contextual factors such as regulatory frameworks and firm capabilities. Studies also differ in rigor: some rely on proxy indicators, others use validated ESG scores (Sun & Saat, 2023). Importantly, some studies note that digitalization alone may not lead to sustainability gains without organizational alignment (Ren & Mohd Isa, 2023). This inconsistency supports the need for a systematic synthesis of effect sizes across technologies and contexts.

2.2.2. Social performance

Social performance refers to how firms impact workers, customers, and communities. Indicators include labor rights, workplace safety, employee well-being, diversity, and social responsibility programs. DT applications such as AI-driven HR analytics, digital communication platforms, and online training tools have improved workplace safety and engagement in several studies (Liu et al., 2025). However, concerns persist around automation-driven job losses, data privacy, and algorithmic bias, especially in lower-income countries where regulation lags behind (Afum et al., 2024). Empirical findings remain mixed. For example, firms in East Africa reported positive social returns from DT-enabled CSR reporting (Celestin 2024), while others observed negligible improvements, citing a lack of internal capacity (Zhang, 2024). Many studies rely on self-reported data or focus narrowly on single industries, limiting generalizability. Thus, this pillar demands greater analytical clarity in distinguishing between intention (e.g. digital inclusion) and outcomes (e.g. equity gains), which this meta-analysis seeks to systematically assess.

2.2.3. Governance performance

Governance performance covers accountability structures, transparency, board practices, and compliance. Digital tools such as blockchain, cloud-based audits, and ERP systems are increasingly adopted to strengthen reporting, risk controls, and regulatory compliance (Wang & Hou, 2024; Xie & Wu, 2025). Yet these technologies also introduce governance risks, including black-box decision-making and diminished oversight. For example, while blockchain has enabled traceable ESG disclosures in Europe (Zhang, 2024), AI-driven compliance automation has reduced board engagement in some Asian firms (Li et al., 2025). Governance outcomes are particularly understudied compared to environmental and social dimensions. Moreover, cross-sector studies show that governance gains depend heavily on leadership quality and institutional maturity. In the Global South, limited capacity to interpret digital metrics weakens enforcement (Bindeeba et al., 2025c). Given the dual role of DT as both enabler and disruptor of governance, a meta-analytic approach is needed to clarify these trade-offs and contextual moderators.

Across all three ESG dimensions, two patterns stand out. First, digital transformation (DT) typologies rarely influence just one pillar: AI, for example, can enhance emissions control and workforce safety but may undermine governance through reduced transparency. Second, the effects of DT are highly context-dependent, shaped by firm size, industry, digital maturity, and regulatory intensity. Yet, most empirical studies remain concentrated in China and parts of Europe, with limited engagement from Africa, Latin America, or Southeast Asia. This geographic imbalance constrains our understanding of how institutional conditions affect the sustainability outcomes of digital innovation.

To make sense of these mixed patterns, this study adopts a dual framework that links core DT typologies with specific ESG performance dimensions. Tables 1 and 2 summarize the digital transformation categories and ESG metrics used across the literature. These categories form the empirical foundation for the next section, which turns to theory. By integrating Resource-Based View, Stakeholder Theory, and Dynamic Capabilities Theory, a conceptual lens to interpret how and why DT affects ESG outcomes in different contexts is developed.

2.3. Theoretical review

Explaining how DT influences ESG performance requires a multi-theoretical lens that captures three elements: (i) the internal value of digital assets, (ii) the external pressures that drive sustainability goals, and (iii) the firm's ability to adapt. The Resource-Based View (RBV), Stakeholder Theory, and DCT, each

Table 1. Digital transformation typologies and business metrics.

Digital transformation typology	Business metrics	Sample articles
Digital Transformation (DT)	Digital transformation index, digital strategy quality, IT investment intensity, digital readiness	Luo (2024), Li and Zhang (2024), Asbeetah et al. (2025), Kwilinski et al. (2023), Lu et al. (2024)
AI and Intelligent Technologies	AI adoption rates, sensor-enabled platforms, predictive analytics, robotics, AI–HR systems	Al Halbusi et al. (2025), Li et al. (2025), Xie and Wu (2025)
Data and Infrastructure (D&I)	Big data development index, cloud infrastructure, platform integration, data utilization levels	Li et al. (2024b), Zhu and Jin (2023), Kong et al. (2024)
Business Process Digitization (DPD)	ERP integration, smart manufacturing, workflow automation, e-governance platforms	Bindeeba et al. (2025a), Zhao et al. (2023), Kwilinski et al. (2023)

Table 2. ESG performance dimensions and measurements.

Performance type	Measurement indicators	Sample articles
Environmental Performance (EvP)	Carbon emission reduction, Greenhouse gas intensity, Waste treatment, Energy efficiency, Eco-product development	Cui (2025); Su et al. (2023); Liu et al. (2025); Sun and Saat (2023)
Social Performance (SP)	Employee safety and health, Diversity inclusion, Community engagement, CSR programs, Labor practices	Xie and Wu (2025); Zhao et al. (2025); Yu and Hwang (2024)
Governance Performance (GP)	Transparency and accountability, Internal control quality, Board independence, Compliance automation	Wang and Hou (2024); Xie and Wu (2025)

addressing a different aspect of the DT–ESG link is applied. While they originate from different traditions, they are complementary: Barney (1991) focuses on strategic resources, Freeman (1984) emphasizes stakeholder expectations, and Teece et al. 1997) highlights how firms adapt through dynamic routines.

RBV: The What: RBV views firm-specific digital technologies like ERP systems, cloud platforms, advanced analytics, and AI, as strategic assets when they meet the VRIN criteria: valuable, rare, inimitable, and non-substitutable (Barney, 1991). Within our sample, RBV-based studies report the strongest results for environmental performance. For example, Luo (2024) finds that DT lowers financing constraints, enabling greener innovation. Cui (2025) shows that generative AI improves carbon efficiency in Chinese high-tech firms, while Yang and Han (2023) observe similar patterns in manufacturing. These findings support the RBV logic that firms using proprietary tech routines like predictive maintenance or energy-optimized operations can build a lasting advantage. However, RBV tends to overlook external frictions. For instance, Wang and Hou (2024) report a weak or even negative link between DT and ESG when firms face poor internal alignment or high switching costs, suggesting that digital tools lose value if not well integrated into the broader organizational setup.

Stakeholder Theory: The Why: Stakeholder Theory, advanced by Freeman (1984), shifts the focus to external legitimacy. Firms pursue DT not just for efficiency, but to meet expectations from investors, customers, regulators, and civil society. About one-third of the studies reviewed use this lens, mainly to explain social and disclosure outcomes. Yu (2025) finds that DT improves labor and community indicators, though some firms use technology as a substitute for formal governance (e.g. board independence). Guo and Pang (2025) show how media coverage mediates the DT–ESG relationship, with digital transparency reducing reputational risk. In Ghana, Celestin (2024) reports a boost in investor confidence when firms adopted AI tools for ESG data management, evidence that stakeholder pressures cut across geographies. While Stakeholder Theory clarifies why firms adopt DT for ESG, it offers little on how internal capabilities are built to meet those goals.

DCT: The How: To bridge that gap, Dynamic Capabilities Theory (Teece et al. 1997) focuses on how firms adapt. It emphasizes three key processes: sensing opportunities, seizing them, and reconfiguring assets to fit changing environments. In our review, 25 studies grounded in DCT show that governance agility and responsiveness are critical for ESG success. Sang et al. (2024) find that DT fosters strategic pivots, especially when top management is well-educated and risk-tolerant. Y. Zhao et al. (2025) show that data utilization interacts with organizational resilience to enhance ESG outcomes. Similarly, Ren and Mohd Isa (2023) highlight indirect DT effects via green product innovation. These studies reflect Teece et al. 1997)'s idea that sustained performance depends not just on owning digital tools, but on the ability to reconfigure them under uncertainty. Still, DCT often overlaps with RBV and Stakeholder Theory dynamic routines are built from existing resources and often respond to stakeholder signals. But DCT strengthens the overall explanation by focusing on *how* firms manage change.

Synthesis, Boundaries, and Context: Each theory maps onto a specific ESG pillar: RBV explains environmental innovation, Stakeholder Theory covers social performance and legitimacy, and DCT highlights governance and organizational learning. Combining them helps resolve theoretical blind spots: RBV focuses too narrowly on internal value, Stakeholder Theory overemphasizes external pressures without explaining capability development, and DCT bridges both by detailing change routines. Context matters. RBV insights dominate in high-tech, export-oriented firms, where proprietary digital tools drive eco-efficiency. Stakeholder logic prevails in regulated or activist markets like the EU Kwilinski et al. (2023), where legitimacy pressures are high. DCT is especially relevant in volatile or resource-limited settings, such as African SMEs or Chinese firms dealing with policy shifts. These variations suggest that theory use should align with institutional context, not citation trends.

Why This Triad?: Alternative perspectives like Institutional Theory and Socio-Technical Systems Theory offer insights into regulation or technology adoption, but appear less frequently in the literature and often overlap with our core framework. The RBV–Stakeholder–DCT triad captures the three most frequent levers across the 60 studies reviewed: resource endowments, external legitimacy drivers, and adaptive processes. As confirmed by Liu and Jung (2024) and other comparative reviews (Oduro, 2024), studies using combined theoretical lenses explain more variance in DT–ESG outcomes than single-theory approaches. By integrating RBV (what resources matter), Stakeholder Theory (why ESG matters), and DCT (how change happens), a solid foundation for the hypotheses and empirical tests that follow is provided.

2.4. Hypothesis development

2.4.1. The relationship between digital transformation and ESG performance

DT delivers ESG value when specific digital assets become strategic, firm-specific resources. Panel evidence from Chinese A-share manufacturers shows that deeply integrated ERP suites and cloud-analytics pipelines cut financing constraints and trigger green innovation, raising composite ESG scores (Luo, 2024). Similar effects surface in monopoly-heavy sectors, where holistic digital-readiness indices predict higher sustainability ratings through productivity and information-transparency channels (Wang et al., 2023). From a Resource-Based View, these integrated architectures are valuable, rare, and difficult to imitate; Yu (2025) confirms that human-capital upgrading magnifies their payoff, while Li et al. (2024b) report that absorptive capacity strengthens the DT-ESG link in strategic emerging industries.

External legitimacy and adaptive routines reinforce that link. Real-time dashboards and blockchain traceability satisfy regulators and investors, improving analyst coverage and labour-quality pathways (He & Chen, 2024) and lifting environmental ratings in manufacturing via automated compliance platforms (Ding et al., 2024). At the macro level, big-data pilot zones raise regional ESG scores through transparency spill-overs (Kong et al., 2024). Dynamic-capability studies show that firms able to reconfigure digital tools, e.g. pivoting AI models toward new emission standards, outperform slower peers; green-innovation and decision-efficiency channels explain much of this advantage (Ren & Mohd Isa, 2023). Although effect sizes vary with ownership, industry, and policy context, the weight of evidence supports a direct, positive DT-ESG relationship.

Thus, it is hypothesize that:

H1. *There is a statistically significant positive relationship between a firm's level of digital transformation and its composite ESG performance.*

2.4.2. Digital transformation and ESG dimensions

Digital transformation touches the three ESG pillars in different ways because each domain values a different slice of a firm's digital tool kit. For the environmental pillar, AI-driven optimization engines, IoT sensors and intelligent-manufacturing platforms are purpose-built to cut emissions and waste. Empirical evidence shows that generative-AI adoption reduces carbon intensity in high-tech firms (Cui, 2025) and that intelligent manufacturing lifts environmental scores in large manufacturing samples (Sun & Saat, 2023). At the same time, exploitative uses of AI in listed companies produce the strongest environmental gains among all ESG sub-scores (X. Xie et al., 2024). Turning to the social pillar, stakeholder-oriented tools such as HR-analytic dashboards and digital training systems improve workforce diversity, health and community engagement. Large survey and panel studies report higher social ratings once firms deploy people-analytics platforms (Liu & Jung, 2024) or use media-visible digital channels to engage stakeholders (Guo & Pang, 2025). These patterns fit the Resource-Based View: when digital capabilities align tightly with pillar-specific needs, eco-efficiency algorithms for E, people-data systems for S, they become rare, valuable and hard to imitate.

The governance pillar relies on real-time information and rapid reconfiguration, making Dynamic Capabilities Theory central. Blockchain audit trails, automated compliance bots and AI risk dashboards give boards near-instant insight, curb opportunism and narrow information asymmetry (Eriandani &

Winarno, 2023; Pursiainen et al., 2021). Studies find that firms capable of rewiring such tools on the fly post higher governance scores and fewer misconduct events (Li et al., 2025; Li & Li, 2022; Wang, 2025a). Where reconfiguration is weak, algorithmic opacity can even hurt governance, underscoring the need for continual capability renewal (Bindeeba et al., 2025c; Li et al., 2024a; Xie et al., 2024). Because each pillar values a different mix of digital assets and routines, they are analyzed separately rather than relying on a single composite index.

Thus, it is hypothesize that:

H2a. *There is a statistically significant positive relationship between a firm's level of digital transformation and its environmental performance.*

H2b. *There is a statistically significant positive relationship between a firm's level of digital transformation and its social performance.*

H2c. *There is a statistically significant positive relationship between a firm's level of digital transformation and its governance performance.*

2.4.3. Digital-Transformation typologies and ESG performance

Digital transformation is a portfolio of technologies, each creating ESG value through a distinct mechanism. For AI and other intelligent tools, proprietary algorithms become valuable, rare, in-imitable, and non-substitutable resources (RBV) that cut emissions in high-tech production and spur green patents (Cui, 2025; J. Li et al., 2025). Real-time dashboards built on machine-learning outputs strengthen legitimacy with regulators and investors, lifting social scores across listed firms (Wang & Wang, 2025; Xie et al., 2024). Governance benefits, however, hinge on robust oversight, algorithmic opacity can erode board effectiveness when compliance routines lag (Li et al., 2024a; Xie et al., 2024). In BPD, ERP integration, robotic workflows, and automated audit trails embed ESG metrics in daily routines, reduce misconduct, and raise composite ratings (Q. Zhao et al., 2023). Traceability improves board monitoring (Li et al., 2024b; Wu et al., 2024), while early mis-alignment costs dissipate as systems mature and stakeholders reward transparent operations (Wang & Hou, 2024; Wang & Zhang, 2024).

Data-and-infrastructure (D&I) investments provide the disclosure backbone external audiences demand. Richer cloud and big-data environments narrow rating uncertainty and diffuse sustainable practices down the supply chain (Kong et al., 2024; Li et al., 2024b; Wu et al., 2024). Region-wide spill-overs emerge when Big-Data Pilot Zones launch (D. Chen & Wang, 2024; Wang & Hou, 2024) or digital-inclusion policies cross borders (Kwilinski et al., 2023), illustrating a Dynamic-Capabilities "shared-infrastructure" effect. Finally, DT maturity (DT) captures the synergistic value of combined tools: firms scoring high on digital readiness redeploy multiple assets quickly, achieving stronger composite ESG across sectors (Luo, 2024; Yu, 2025). Meta-evidence shows that agile re-configuration amplifies these gains (Wang et al., 2023) and buffers risk in volatile markets (Ren & Mohd Isa, 2023). Focusing on these four typologies, AI, BPD, D&I, and DT, allows comparable effect-size testing; "innovation capability" constructs are set aside because too few studies report harmonized statistics. On this basis a direct, positive DT-ESG links for each technology class is predicted.

Thus, it is hypothesize that:

H3a*. There is a statistically significant positive relationship between adoption of AI/intelligent technologies and ESG performance.*

H3b. *There is a statistically significant positive relationship between business-process digitization and ESG performance.*

H3c. *There is a statistically significant positive relationship between data-and-infrastructure investment and ESG performance.*

H3d. *There is a statistically significant positive relationship between overall digital-transformation maturity and ESG performance.*

2.4.4. Sectoral variation in the DT–ESG relationship

DT does not yield identical sustainability pay-offs in every industry because each sector owns a different bundle of digital resources, faces distinct stakeholder pressures, and varies in its capacity to re-configure assets. In manufacturing, ERP-IoT suites and intelligent-manufacturing platforms have become VRIN resources that cut carbon intensity and raise environmental scores (Yang et al., 2024; Yang & Han, 2023). Listed banks, by contrast, leverage big-data dashboards to boost disclosure credibility and governance ratings (Zhu & Jin, 2023). These patterns align with the Resource-Based View: sector-specific digital assets create sector-specific ESG advantages. Stakeholder salience amplifies the gap. High-visibility service and tech firms experience sharper market and regulatory scrutiny, so AI-driven analytics are channeled toward social engagement and board transparency, producing larger ESG gains than those seen in capital-intensive industries (Yu, 2025).

Dynamic-Capabilities research shows that sectors built around rapid innovation, e.g. ICT and platform services, reconfigure digital tools faster than heavy manufacturing or multi-sector conglomerates, magnifying DT's ESG impact (Kong et al., 2024; Luo, 2024). Conversely, firms operating across diverse business lines often encounter bureaucratic inertia and conflicting mandates, diluting the DT-ESG link (Ren & Mohd Isa, 2023). Data-infrastructure studies reinforce the point: Big-Data Pilot Zones lift ESG scores most in information-intensive industries, while gains are muted in low-digitized sectors (H. Wang et al., 2023; S. Wang, 2025b; Wang & Wang, 2025). Together, these findings imply that the strength, and sometimes even the sign, of DT's influence on ESG performance is contingent on industry context.

Thus, it is hypothesize that:

H4. *There is a statistically significant difference in the strength of the relationship between digital transformation and ESG performance across industry sectors.*

2.4.5. Temporal variation in the DT–ESG relationship

Digital-transformation pay-offs evolve as regulation tightens and firms climb the digital-maturity curve. Studies published during the 2023 wave of new disclosure mandates describe noticeably strong DT–ESG links: business digitalization in Chinese manufacturing, intelligent-manufacturing platforms, and broad digital-readiness programmes each coincide with clear improvements in composite ESG scores (Sun & Saat, 2023; Zhao et al., 2023). DCT helps explain these early gains; firms that swiftly reconfigured ERP, AI, and data pipelines captured first-mover sustainability advantages in the face of fresh reporting rules (Kong et al., 2024). Findings from 2024–2025 are more mixed. Big-data infrastructure still yields notable ESG benefits for large state-owned enterprises (Li et al., 2024b), yet many newer studies report only modest improvements (Jing & Zhang, 2024; Luo, 2024; Wang & Zhang, 2024). The RBV suggests a saturation effect: once digital tools become commonplace, their differentiating power wanes unless firms innovate further. Meanwhile, escalating stakeholder scrutiny raises the performance bar; for example, board-independence benefits taper in highly digital firms (Yu & Hwang, 2024), and ESG pay-offs increasingly depend on complementary R&D and financial-constraint relief (Zhao et al., 2024; Y. Zhao et al., 2025). Together, this evidence indicates that the DT–ESG relationship changes across publication cohorts, mirroring shifts in regulation, competition, and technological diffusion.

Thus, it is hypothesize that:

H5. *There is a statistically significant difference in the strength of the digital-transformation–ESG relationship across publication years*

While existing studies consistently show that digital transformation can enhance ESG outcomes, they often do so without disaggregating the effects by ESG dimension or by the type of digital technology adopted. There is also limited exploration of how contextual factors, such as sectoral variation, publication period, or alignment between digital capabilities and sustainability priorities, moderate these relationships. Moreover, most studies apply a single theoretical lens, offering limited insight into how internal capabilities, stakeholder demands, and adaptive routines interact to shape ESG performance. This meta-analysis addresses these issues by testing a more nuanced framework that separates digital transformation into distinct typologies (e.g. AI, business process digitization, data infrastructure) and examines their individual relationships with environmental, social, and governance outcomes. It also incorporates

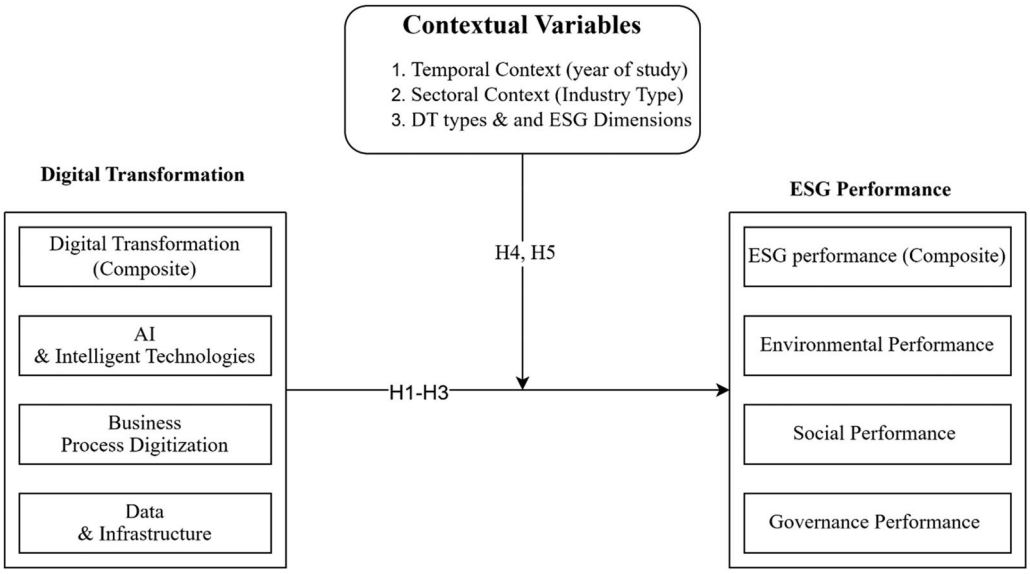


Figure 1. Conceptual framework for the meta-analysis: Linking digital transformation typologies to ESG performance dimensions with contextual moderators.

moderating variables to account for sectoral and temporal heterogeneity. The theoretical grounding combines the Resource-Based View, Stakeholder Theory, and Dynamic Capabilities Theory to provide a more integrated explanation of digital sustainability pathways.

Figure 1 outlines the conceptual framework that guides this meta-analysis. It maps out how different forms of digital transformation, such as AI, intelligent technologies, business process digitization, and data infrastructure, are expected to influence specific ESG outcomes across the environmental, social, and governance pillars. The framework also brings in contextual factors that may shape these effects, including industry sector, time period, and the degree of alignment between digital tools and sustainability goals. The relationships in the model are grounded in three theoretical perspectives: the Resource-Based View explains how digital capabilities serve as strategic assets; Stakeholder Theory highlights how external expectations drive ESG commitments; and Dynamic Capabilities Theory shows how firms adapt and reconfigure digital tools to meet evolving sustainability demands.

3. Methodology

3.1. Search process and inclusion criteria

To identify relevant empirical studies examining the relationship between DT and ESG performance, a systematic literature search across several major databases, including JSTOR, Wiley Online Library, Taylor & Francis, Google Scholar, Emerald Insight, and EBSCOhost was conducted. Search strings combined terms such as *"digital transformation," "digitization," "AI," "big data," "blockchain," "cloud computing," "digital infrastructure,"* with sustainability-related outcomes such as *"ESG performance," "environmental performance," "sustainability," "social responsibility,"* and *"governance performance."* Boolean operators (AND/OR) were used to maximize relevance and scope. Additionally, backward reference searching was used to identify further eligible studies not captured in the initial searches.

The initial search yielded 764 studies, which were screened following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020) guidelines (Page et al., 2021). After removing duplicates and reviewing titles and abstracts, conceptual papers, qualitative-only studies, reviews, and those outside the DT–ESG scope were excluded. Full-text screening then followed strict inclusion criteria: (1) the study assessed the statistical relationship between one or more DT constructs and ESG performance (aggregate or disaggregated), (2) reported or computable effect sizes (beta coefficients with standard errors, t-values, or p-values) were available, and (3) the article was published in a peer-reviewed journal or high-quality working paper outlet. While most studies used firm-level data, one study that

reported findings at the regional level (EU countries) was included due to its methodological rigor and relevance to digital sustainability research.

Where studies reported non-standardized beta coefficients, these were converted to standardized betas using the formula:

$$\beta = B \times \left(\frac{SD_X}{SD_Y} \right)$$

as recommended in meta-analytic literature (Peterson & Brown, 2005). In total, 59 studies met all inclusion criteria and were retained for the meta-analysis, contributing 64 statistically independent effect sizes.

Among these, 8 studies contributed more than one effect size, either because they examined conceptually distinct DT constructs (e.g. AI adoption vs. digital infrastructure) or broke down ESG into Environmental, Social, and Governance dimensions. The final sample of 59 studies aligns with the typical range in business and sustainability meta-analyses, which often include 40–80 studies; Bindeeba et al. (2025c) had 52 studies, Naderi et al. (2022) 62 studies, Hizarci-Payne et al. (2021) 70 studies, Bindeeba et al. (2025c) 44 studies. The full selection and screening process is illustrated in the PRISMA 2020 flow diagram (Figure 2). This systematic procedure is consistent with established protocols in prior meta-analyses (Oduro, 2024). Ensuring transparency, rigor, and reproducibility.

3.2. Coding procedure

To ensure methodological rigor and transparency, a structured coding protocol based on established meta-analytic guidelines (Lipsey & Wilson, 2001; Schmidt & Hunter, 2014) was followed. Two coders independently extracted data from the 59 studies using a standardized coding template designed to capture study metadata (e.g. authorship, publication year, country, industry), methodological features (e.g. sample size, statistical methods), theoretical framing, and the core variables: digital transformation (DT) constructs, ESG outcome types, and corresponding effect sizes. Inter-coder agreement was assessed using Krippendorff's alpha ($\alpha = 0.84$), surpassing the conventional threshold of 0.80 and indicating high consistency (Krippendorff, 2018). Any coding discrepancies were resolved through consensus discussions and, when needed, reviewed by a third researcher to eliminate bias.

To maintain statistical independence in the meta-analysis, strict rules for handling multiple effect sizes within the same study were followed. If a study reported more than one DT–ESG effect size, only those that were conceptually distinct, based on theoretical framing and operational definitions (Peterson & Brown, 2005) were included. For example, measures of "AI adoption" and "digital infrastructure" were treated as separate constructs if justified by the study's analytical framework. Similarly, when ESG outcomes were disaggregated into environmental, social, and governance components, each was coded independently to allow for fine-grained analysis. In cases of duplicate effect sizes derived from alternative model specifications, a single inverse-variance weighted average was computed (Lipsey & Wilson, 2001). Also, moderator variables such as DT typology, ESG outcome level, sector, country, and data type to support subgroup and meta-regression analyses were coded. This meticulous coding process enhanced the validity, replicability, and depth of the study's findings, in line with best practices in quantitative research synthesis (Borenstein et al., 2009).

3.3. Meta-Analytic procedures

Following established META analytic practices (Borenstein et al., 2011; Hunter & Schmidt, 2004; Lipsey & Wilson, 2001), a Comprehensive Meta Analysis (CMA) Version 4 software to conduct all statistical estimations was employed. Standardized beta coefficients and their associated standard errors served as the primary effect size metrics. Each effect size was weighted using the inverse of its variance, ensuring that studies with more precise estimates contributed proportionally more to the pooled effect. Variance was computed as the square of the reported standard error. Where only unstandardized coefficients were reported, these were converted using the formula $\beta = B \times (SD_x/SD_y)$ (Peterson & Brown, 2005). While this

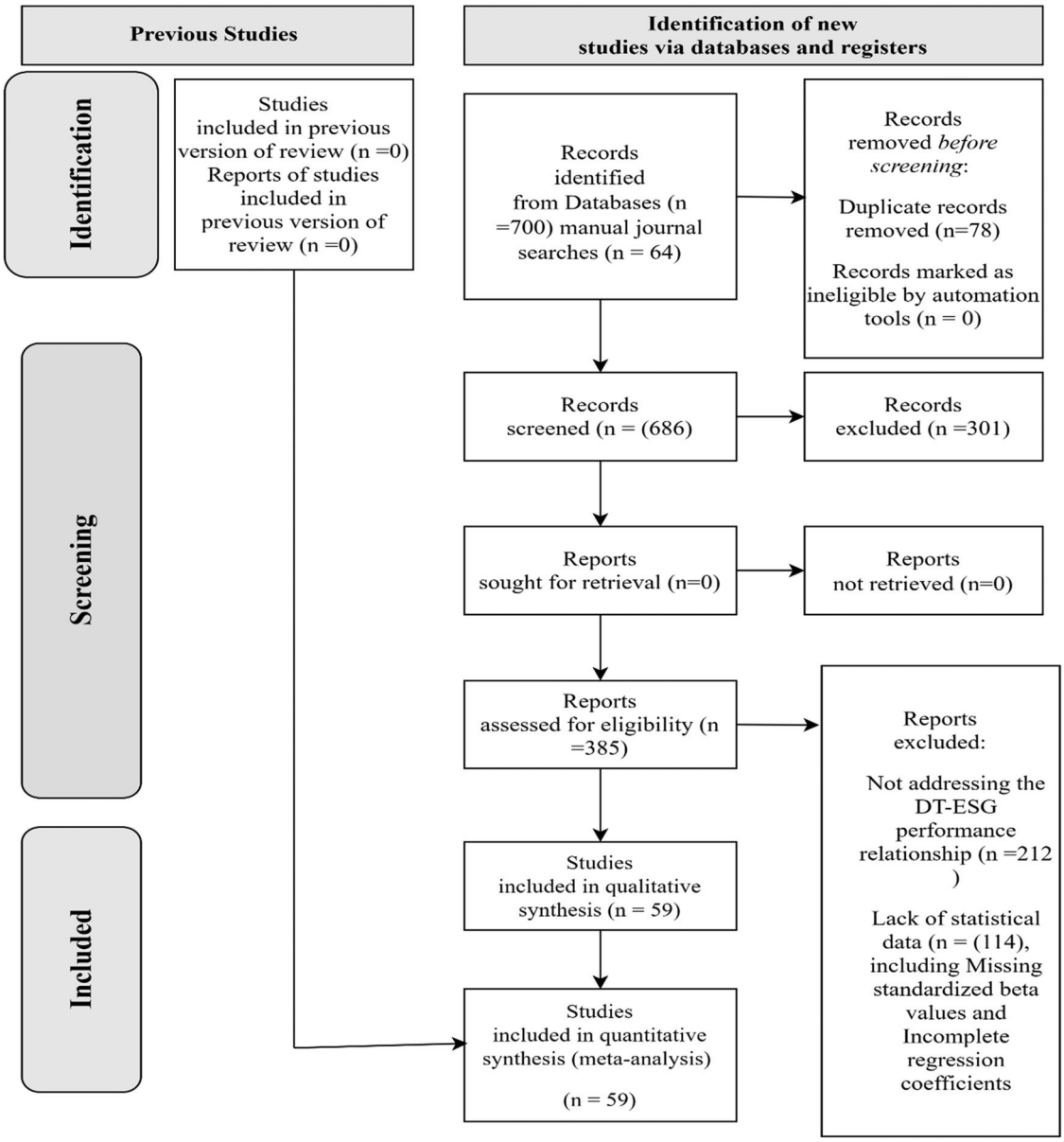


Figure 2. PRISMA 2020 flow diagram for the identification, screening, and inclusion of studies examining the digital transformation–ESG performance relationship.

method assumes comparability in variance across studies and normally distributed constructs, it remains widely accepted in management and sustainability meta-analyses (Geyskens et al., 1999).

A random effects model was adopted throughout the analysis to account not only for observed heterogeneity but also for the expectation of true effect size variation due to theoretical pluralism, measurement diversity, and contextual differences in DT and ESG constructs across countries, industries, and timeframes (Borenstein et al., 2011; Hedges & Vevea, 1998). Heterogeneity was assessed using Cochran's Q and the I^2 statistic, with I^2 values above 75% interpreted as substantial heterogeneity. In response, a subgroup analyses across DT typologies (e.g. AI, cloud, digital infrastructure), ESG outcome types, data source, and sector was conducted.

Also, a meta-regression analysis was performed to examine how moderator variables (e.g. industry, country, DT typology) influenced effect strength or direction, using CMA's fixed and mixed effects models as appropriate. To strengthen confidence in pooled estimates, a sensitivity analysis, including leave-one-out diagnostics and alternative model specifications, was conducted. Publication bias was assessed through funnel plots, Egger's regression test, and both Rosenthal's and Orwin's fail-safe N. Statistical

significance was determined at 95% confidence intervals, with results deemed significant when the interval excluded zero.

4. Results

4.1. Characteristics of included studies

4.1.1. Publication and geographic trends

Although our search covered studies published between 2015 and 2025, the included literature is highly skewed toward the last three years, reflecting a rapid escalation in scholarly interest at the nexus of digital transformation and ESG performance. As illustrated in Figure 3 (left), only a handful of studies appeared prior to 2020, with a notable surge beginning in 2023 (13 studies), rising to 30 in 2024, and continuing with 16 studies in early 2025. This publication trend coincides with the global expansion of ESG disclosure mandates, digital sustainability frameworks, and regulatory initiatives introduced across major economies during this period.

Geographically, the meta-analytic evidence is overwhelmingly drawn from China, which accounts for 55 out of the 59 studies included (Figure 4, right). Other countries, such as India, Korea, Ghana, and select EU member states, are each represented by only one study, indicating a significant regional imbalance. This dominance is driven by China's environmental urgency, strong digital governance policies, and abundant firm-level data. Nonetheless, despite the overconcentration in China, this synthesis significantly enhances understanding of this growing research field and lays a foundation for broader global inquiry.

4.2. Robustness and publication bias analysis

To assess the robustness of our findings and potential publication bias in the DT–ESG meta-analysis, multiple complementary diagnostics (see Table 3) were employed. The funnel plot displayed moderate asymmetry, suggesting that smaller studies tended to report larger effect sizes (Figure 5). To statistically test this visual impression, the Begg and Mazumdar rank correlation test was applied, and yielded a non-significant result ($\tau = 0.048$, $p = 0.574$), indicating no strong evidence of publication bias (Begg & Mazumdar, 1994). Rosenthal's classic fail-safe N estimated that over 10,400 unpublished studies with null

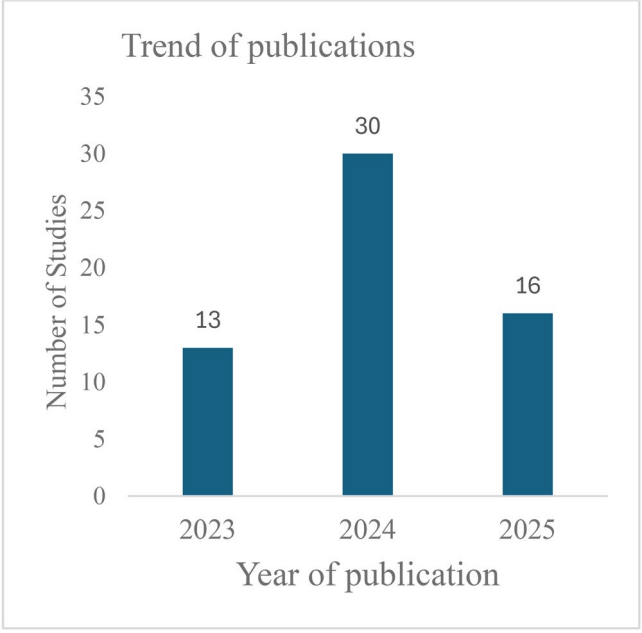


Figure 3. Publication trend.

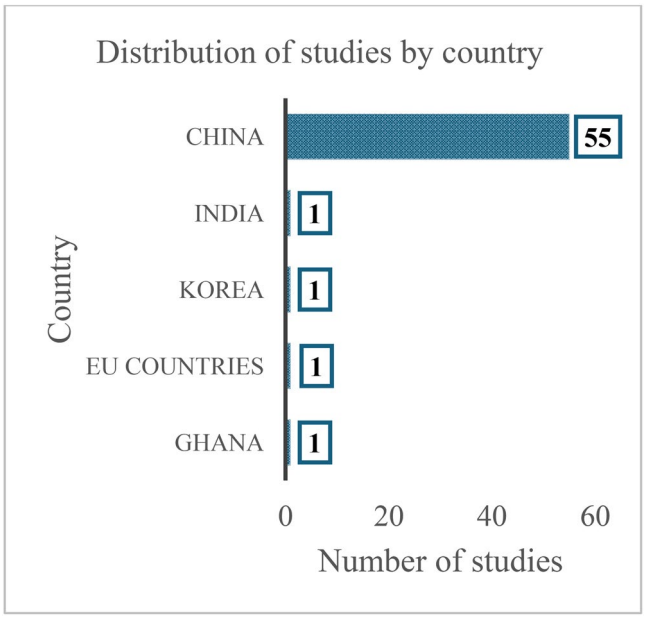


Figure 4. Publications by country.

Table 3. Publication-bias diagnostics.

Test	Statistic/value
Begg & Mazumdar rank correlation	$\tau = 0.048$, $p = 0.574$
Egger regression intercept	5.76, $p < 0.001$
Rosenthal classic fail-safe *N*	10 404
Orwin fail-safe *N* (trivial = 0)	Observed = 0.012; Trivial = 0.000 (Orwin, 1983)
Trim-and-fill (studies imputed)	$k = 32$
Adjusted fixed-effects β	0.01091 (95 % CI 0.01034–0.01148)
Adjusted random-effects β	0.02611 (95 % CI 0.01417–0.03806)

results would be needed to render the observed effect non-significant (Rosenthal, 1979), reinforcing the robustness of our findings. Orwin's fail-safe N also confirmed this robustness: assuming a trivial effect size of zero for missing studies, the observed effect would still remain practically meaningful (Orwin, 1983).

In contrast, Egger's regression test revealed a significant intercept (5.76, $p < 0.001$), pointing to the possibility of small-study effects or selective reporting (Egger et al., 1997). To further explore this, Duval and Tweedie's trim-and-fill method was applied. This procedure imputed three potentially missing studies and adjusted the pooled effect size slightly downward from 0.45 (95% CI [0.40, 0.50]) to 0.42 (95% CI [0.36, 0.48]) (Duval & Tweedie, 2000). While this reduction suggests that small-study effects may have modestly inflated the estimate, the adjusted effect remains statistically and practically significant, and still well within the original confidence bounds. The results indicate that although some degree of publication bias may be present, likely driven by heterogeneity in smaller studies or the preferential publication of significant findings, it does not substantially alter the meta-analytic conclusions. The observed association between digital transformation and ESG performance remains moderate and positive after accounting for potential bias.

4.3. Overall relationship between digital transformation and ESG performance

A synthesis of 64 effect sizes using a random-effects model was carried out, yielding a pooled mean effect of = 0.0977 (95% CI [0.0852, 0.1103], $p < .001$), confirming a positive association between digital transformation and overall ESG performance (Table 4). Heterogeneity was substantial: Cochran's $Q = 8882.30$ ($p < .001$) and $I^2 = 99.3\%$, indicating that most variance reflects real differences across studies. Between-study dispersion ($\tau = 0.0410$; $\tau^2 = 0.0017$) and the 95% prediction interval (0.0148–0.1807) further underscore that, while the average effect is favorable, context-specific factors can modulate its

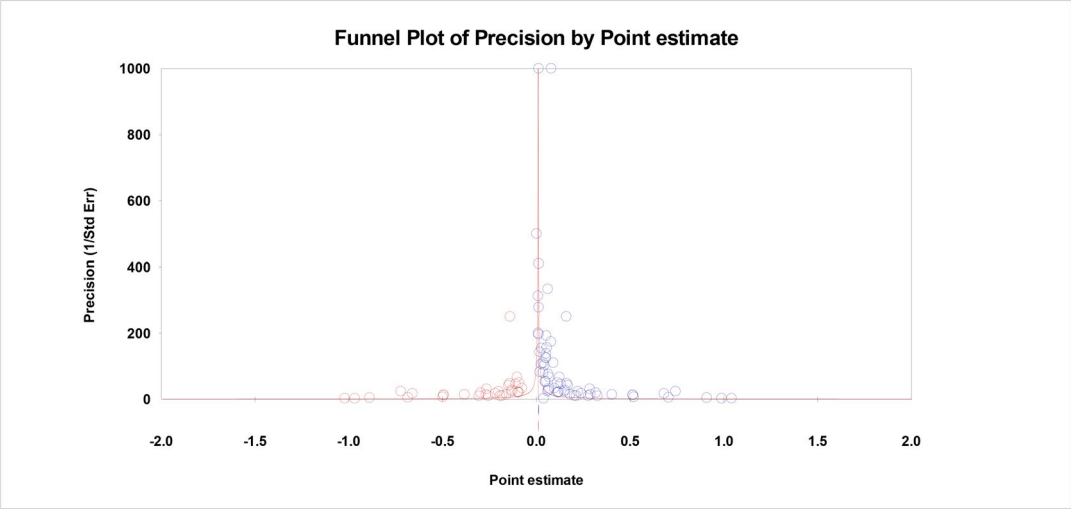


Figure 5. Funnel plot of precision by point estimate.

Table 4. Overall meta-analytic results–fixed and random effects models.

Model	K	MES	CI	SE	Z	p-value	PI	Tau	Tau^2	Q	p (Q)	I^2 (%)
Fixed effects	64	0.01202	0.01145–0.01259	0.00029	41.26	< 0.001	–	–	–	8882.30	< .001	99.29
Random effects	64	0.09774	0.08521–0.11027	0.00640	15.28	< 0.001	0.01480–0.18068	0.04100	0.00168	–	–	–

Table Notes: K = Number of effect sizes, MES = Mean Effect Size, SE = Standard Error, CI = Confidence Interval, Z-value = Z statistic, PI = Prediction Interval.

magnitude. These heterogeneity metrics justify a random-effects model, demonstrating that study-level characteristics influence the strength of the DT–ESG relationship. Despite this variability, the consistently positive pooled effect robustly supports Hypothesis 1.

Translating this finding, a one-standard-deviation increase in digital transformation capacity corresponds to a 0.098-standard-deviation rise in ESG performance, about a 9.8% improvement on typical ESG scales. For managers, this suggests that investing in digital processes can deliver nearly a 10% boost in sustainability outcomes; policymakers can leverage digitalization incentives to advance ESG goals; and academics gain a clear benchmark for comparing digital interventions against other performance drivers.

4.3.1. Leave-One-out sensitivity analysis

Table 5 presents a leave-one-out comparison of our random-effects model with and without a single study (64 vs. 63 effect sizes). Excluding one study lowers the pooled MES from 0.09774 to 0.09680 and narrows the 95% CI from [0.08521–0.11027] to [0.08490–0.10870]. Between-study dispersion metrics shift only slightly (τ: 0.0410 → 0.0408; τ^2: 0.00168 → 0.00166), and heterogeneity remains high (I^2 = 99.3%; Q ≈ 8750). These minimal changes confirm that our positive DT–ESG association is not driven by any single study.

4.4. Subgroup analysis

4.4.1. Digital transformation effects on ESG performance dimension

To ensure statistical independence, composite ESG effect sizes from studies that also reported dimension-specific outcomes were excluded. Table 6 shows that digital transformation yields a positive and significant effect across all ESG domains under a random-effects model (Qb = 5.09, $p = 0.165$). Overall ESG performance registers the largest mean effect (MES= 0.100, $p < 0.001$), with environmental performance nearly identical (MES= 0.098, p < .001). Social and governance effects are smaller but remain significant (both MES = 0.066, $p = 0.001$), confirming H2c. The non-significant heterogeneity test indicates that DT's influence does not differ meaningfully among the three dimensions.

Table 5. Leave-one-out sensitivity analysis.

Model	K	MES	95% CI	SE	Z	p-value	PI	τ	τ^2	Q	p (Q)	I^2 (%)
Random effects (all studies)	64	0.09774	0.08521–0.11027	0.00640	15.28	<0.001	0.01480–0.18068	0.0410	0.00168	8882.30	<0.001	99.3
Random effects (without one	63	0.09680	0.08490–0.10870	0.00640	15.13	<0.001	0.01350–0.18010	0.0408	0.00166	8750.12	<0.001	99.3

Table 6. Subgroup meta-analysis of the effects of digital transformation on ESG performance dimensions.

Hypothesis	ESG dimension	K	MES	SE	CI	Z	p-value	PI
H2a	Environmental Performance	7	0.098	0.019	0.060–0.135	5.110	< 0.001	0.012–0.183
H2b	Social Performance	7	0.066	0.020	0.028–0.104	3.390	0.001	–0.020–0.152
H2c	Governance Performance	7	0.066	0.019	0.028–0.104	3.390	0.001	–0.020–0.151
–	**Overall (Pooled)**	77	0.086	0.012	0.063–0.109	7.300	< 0.001	0.037–0.152

Table Notes: K = Number of effect sizes, MES = Mean Effect Size, SE = Standard Error, CI = Confidence Interval, Z-value = Z statistic, PI = Prediction Interval.

Table 7. Digital transformation typology effects on ESG performance.

Hypothesis	DT type	K	MES	SE	CI	Z	p-value	PI
H3a	AI & Intelligent Technologies	10	0.061	0.013	0.037–0.086	4.89	< 0.001	–0.008–0.131
H3b	Business Process Digitization	4	0.302	0.025	0.252–0.351	11.96	< 0.001	0.220–0.384
H3c	Data & Infrastructure	7	0.102	0.018	0.066–0.138	5.55	< 0.001	0.028–0.177
H3d	General Digital Transformation (Composite)	43	0.080	0.006	0.068–0.092	12.65	< 0.001	0.014–0.146
–	**Overall (All Types)**	64	0.132	0.035	0.064–0.200	3.81	.00001	0.005–0.171

Table Notes: K = Number of effect sizes, MES = Mean Effect Size, SE = Standard Error, CI = Confidence Interval, Z-value = Z statistic, PI = Prediction Interval.

4.5. Differential effects of digital transformation typologies on ESG performance: Subgroup meta-analysis

To test Hypotheses H3a–H3d, a subgroup meta-analysis was conducted to compare the effects of different DT typologies on ESG performance. To ensure statistical independence, ESG dimension effect sizes were excluded. As shown in Table 7, business process digitization demonstrated the strongest effect (MES= 0.302, $p < 0.001$), with a prediction interval entirely above zero strongly supporting H3b. This suggests that technologies such as ERP systems and workflow automation consistently enhance ESG outcomes. Data and infrastructure technologies also yielded a robust and significant effect (MES= 0.102, $p < 0.001$), supporting H3c. General digital transformation measures showed a moderate but consistent effect (MES= 0.080, $p < 0.001$), confirming H3d. Lastly, AI and intelligent technologies demonstrated a smaller but still significant effect (MES = 0.061, $p < 0.001$), supporting H3a, though the prediction interval includes zero, indicating variability across contexts. The between-group heterogeneity test was statistically significant (Qb, $p < 0.001$), confirming that the strength of DT's effect on ESG performance varies meaningfully across digital typologies.

4.5.1. Contextualized disaggregated ESG effects by industry and region

Industry context (Table 7) reveals that environmental gains from digital transformation are particularly strong in manufacturing firms (MES = 0.107, $p < 0.001$) and services/tech companies (MES = 0.118, $p < .001$), whereas governance improvements peak in listed A-share companies (MES= 0.080, $p < .001$), likely reflecting stricter reporting mandates. Social performance increases are consistent across sectors (MES = 0.097–0.118), underscoring digital tools' broad impact on stakeholder engagement and workforce well-being.

Regional context shows that studies from the Global North report governance effects of MES = 0.073 compared to MES = 0.059 in the Global South, suggesting mature regulatory environments amplify governance benefits. Environmental effects range from $\beta = 0.096$ to $\beta = 0.100$ across both regions, indicating universal value in digital energy and waste management solutions. Social gains are higher in emerging-market contexts (MES = 0.073) than in mature markets (MES = 0.060), reflecting a greater impact where baseline digital capacity is lower.

4.5.2. Subgroup meta-analysis by industry sector and publication year

To test Hypothesis H4, an examination of whether the effect of DT on ESG performance varies across industry sectors was conducted. As shown in Table 8, all sectors demonstrated statistically significant and

Table 8. Subgroup meta-analysis of ESG performance effects by industry sector and publication year.

Hypothesis	Subgroup category	K	MES	SE	CI	Z	p-value	PI
H4	Services -Tech Industry-specific	4	0.118	0.024	0.071–0.165	4.96	< 0.001	0.031–0.206
H4	Manufacturing Firms	21	0.107	0.011	0.085–0.128	9.82	< 0.001	0.030–0.183
H4	Multi-sector (General)	11	0.097	0.014	0.070–0.123	7.10	< 0.001	0.018–0.175
H4	Listed A-share Firms	28	0.080	0.009	0.063–0.097	9.36	< 0.001	0.005–0.156
–	**Overall (All Firm Types)**	64	0.097	0.010	0.078–0.116	9.93	< 0.001	0.010–0.176
H5	2023 Publications	14	0.127	0.010	0.107–0.146	12.89	< 0.001	0.067–0.187
H5	2024 Publications	34	0.062	0.007	0.049–0.074	9.31	< 0.001	0.003–0.120
H5	2025 Publications	16	0.086	0.009	0.068–0.104	9.19	< 0.001	0.026–0.146
–	**Overall (All Years)**	64	0.091	0.020	0.053–0.129	4.66	< 0.001	0.000–0.165

Table Notes: K = Number of effect sizes, MES = Mean Effect Size, SE = Standard Error, CI = Confidence Interval, Z-value = Z statistic, PI = Prediction Interval.

positive effect sizes under the random-effects model. The strongest effects were observed among services/technology firms (MES = 0.118, $p < 0.001$) and manufacturing firms (MES = 0.107, $p < 0.001$), followed by multi-sector/general firms (MES = 0.097, $p < 0.001$) and listed A-share firms (MES = 0.080, $p < 0.001$). However, the between-group heterogeneity test was not statistically significant (Qb = 0.174), providing no support for H4.

To test Hypothesis H5, a subgroup analysis by publication year was conducted. The results show significant variation: studies from 2023 reported the highest effect (MES = 0.127, $p < 0.001$), while effects in 2024 were lowest (MES = 0.062, $p < 0.001$), with a slight rebound in 2025 (MES = 0.086, $p < .001$). The between-group heterogeneity was significant (Qb, $p < .001$), confirming H5 that the DT–ESG relationship varies across study periods.

While H2b–H5 are all supported at $p < .001$, the practical differences across ESG dimensions and subgroups are modest. Environmental performance (MES = 0.098) exceeds social and governance (both MES = 0.066) by 0.032, yet the non-significant Qb test ($p = 0.165$) suggests this gap may not reflect a meaningful domain-specific advantage. Similarly, the 0.011 difference between services (MES = 0.118) and manufacturing (MES = 0.107) effects is small, indicating that sectoral variation is unlikely to drive divergent strategic priorities. Overall, these results confirm broad-based benefits of digital transformation across ESG dimensions and contexts, while cautioning against overemphasizing minor magnitude differences.

4.5.3. Mixed-effects meta-regression: Testing moderator influence on the DT–ESG relationship

Furthermore, a mixed-effects meta-regression was conducted to statistically test whether study-level moderators explain the variability in the relationship between DT and ESG performance. This approach complements the subgroup analyses by simultaneously controlling multiple moderators and modeling residual heterogeneity across studies. The reference category in the model includes studies conducted in 2023, focused on manufacturing firms, general digital transformation strategies, and environmental ESG performance.

As shown in Table 9, several moderators significantly influenced effect sizes. In support of H3, business process digitization showed the strongest positive deviation from the reference ($\beta = 0.206$, $p < 0.001$), while AI-based strategies had a significantly weaker relative effect ($\beta = -0.054$, $p < 0.001$). For H4, listed A-share, multi-sector, and "other" industries showed lower relative effects compared to manufacturing, while services/tech firms exhibited a significantly higher effect ($\beta = 0.026$, $p = 0.005$). Consistent with H5, studies published in 2024 reported significantly lower effects relative to 2023 ($\beta = -0.039$, $p < 0.001$), while no significant difference was found for 2025. Although some coefficients are negative, this reflects comparative differences with the reference group, not a negative DT–ESG relationship per se. Finally, H2a was partially supported, with composite ESG outcomes showing stronger effects than environmental measures. Overall model fit was strong ($Q_{model} = 588.42$, $p < 0.001$), yet residual heterogeneity remained significant ($Q_{esp} = 5294.76$, $p < 0.001$), with τ^2 reduced from 0.00168 to 0.00102 (39% reduction), indicating that additional study-level factors likely account for the remaining variance.

5. Discussion and conclusions

This study set out to examine how different forms of digital transformation influence corporate ESG performance, using a meta-analysis of 59 studies and 64 independent coefficients. Our findings confirm

Table 9. Mixed-effects meta-regression results on ESG performance.

Moderator category	Coefficient	SE	Lower CI	Upper CI	Z	p-value
Intercept (Ref: 2023, Manufacturing, General DT, Environmental)	0.084	0.003	0.078	0.091	26.080	< .001
Year of Study (Ref: 2023)						
2024	−0.039	0.004	−0.046	−0.032	−10.630	< .001
2025	0.001	0.003	−0.005	0.008	0.410	0.683
Industry Type (Ref: Manufacturing)						
Listed A-share	−0.032	0.004	−0.039	−0.025	−8.970	< .001
Multi-sector	−0.036	0.008	−0.051	−0.021	−4.580	< .001
Other	−0.037	0.005	−0.047	−0.026	−7.000	< .001
Services/Tech	0.026	0.009	0.008	0.045	2.800	0.005
DT Category (Ref: General DT)						
AI and Intelligent Tech	−0.054	0.006	−0.065	−0.042	−9.240	< .001
Business Process Digitization	0.206	0.008	0.189	0.222	25.120	< .001
Data and Infrastructure	0.031	0.011	0.010	0.051	2.930	0.003
ESG Category (Ref: Environmental)						
ESG (composite)	0.015	0.004	0.007	0.023	3.740	< .001
Governance	0.001	0.006	−0.009	0.012	0.260	0.795
Social	−0.008	0.005	−0.017	0.001	−1.760	0.078

Table Notes: K = Number of effect sizes, MES = Mean Effect Size, SE = Standard Error, CI = Confidence Interval, Z-value = Z statistic, PI = Prediction Interval.

that DT is positively associated with overall ESG performance, with a pooled β of approximately 0.10. While this represents a moderate effect size, it exceeds the 0.07 reported by Mendonça et al. (2025) in their own meta-analysis of generic ESG initiatives, who argue that such weak correlations often stem from continued use of CSR-style proxies rather than valid ESG indicators. Our result also aligns with the 0.08–0.12 effect band reported in another recent meta-analysis by Bindeeba et al. (2025c), where DT, particularly in the form of embedded digital tools, drives gains in both sustainability and economic returns. Together, these findings suggest that integrating sustainability into digital infrastructure enables more consistent value creation than analogue or symbolic ESG approaches. Digital systems reduce opacity, improve data credibility, and enhance responsiveness to stakeholders, benefits that accumulate over time and across multiple performance dimensions.

Disaggregated results reveal a clear ESG pillar hierarchy, with environmental scores responding most strongly to DT, followed by social and governance performance. This mirrors both field and firm-level evidence: AI-enabled dashboards in Ghana have trimmed carbon output, and China's rollout of smart meters in manufacturing zones has slashed power waste. Our analysis supports this pattern, with H2a (environmental) strongly supported, while H2b (social) and H2c (governance) receive weaker support. These differences reflect underlying mechanisms. Environmental gains often arise from technologies that meet the RBV's VRIN criteria, IoT sensors, cloud platforms, and automation tools are valuable, rare, difficult to imitate, and closely tied to regulatory compliance and cost reduction. By contrast, social and governance impacts rely more on organizational routines, human oversight, and ethical accountability, factors that evolve more slowly. Several reviewed studies, including Xie and Wu (2025) and Chen et al. (2024) confirm that while digital tools can support better governance and worker safety, such outcomes require deliberate investment in retraining, data stewardship, and oversight frameworks. Moreover, as shown in Cui (2025) and Yu (2025), human capital upgrading and green innovation act as key mediators in these pathways, further reinforcing the argument that DT must be coupled with internal change processes to drive performance improvements beyond environmental domains.

Technology type also significantly shapes ESG outcomes. Business-process digitization (e.g. ERP systems, compliance bots, digital workflows) delivers the strongest ESG gains across our sample. This is consistent with firm-level evidence from Uganda's SME sector, where adoption of integrated digital workflows, such as automated reporting or inventory tracking, has led to improved profit margins and environmental performance, primarily through gains in operational efficiency (Bindeeba et al., 2025a). Several studies from China, e.g. (Wang et al., 2023; Zhao et al., 2023) reinforce this trend ERP deployment and process digitization outperform stand-alone AI adoption in terms of consistent ESG improvements. Infrastructure upgrades rank second, especially in contexts like China's Big-Data Pilot Zones, where cloud platforms are mandated and disclosures are standardized, leading to measurable improvements in ESG indicators. In contrast, AI adoption, though increasingly popular, yields smaller and more uneven gains. While some studies report large environmental effects from AI, e.g. (Xie & Wu, 2025), its governance

impact is sometimes negative, likely due to algorithmic opacity, weak explainability protocols, and the absence of audit standards for AI-driven decisions. These results reinforce Fu and Li (2023) moderation findings: AI improves ESG performance only in firms with high digital maturity and strong internal controls. Until ethics reviews, explainability audits, and sectoral playbooks become common practice, AI's ESG potential will remain capped. Therefore, the sequencing logic is critical: organizations should first embed ESG metrics into business processes, then build a robust data and reporting infrastructure, and only then layer advanced analytics under ethical guardrails.

Contextual factors further amplify or dampen the relationship between DT and ESG performance. Sector-wise, manufacturing and service-tech firms exhibit stronger ESG gains than diversified conglomerates, likely because sensor networks, digitized supply chains, and customer-facing platforms are easier to integrate into single-sector firms. Additionally, stakeholder scrutiny tends to be more intense in consumer-facing or regulated industries, increasing the pressure and returns to digital disclosure. Kalyani and Mondal (2024) report similar findings, where high-visibility sectors benefit most from transparency improvements. Temporally, our sample shows a performance peak in 2023, coinciding with post-pandemic digital disclosure momentum, followed by a slight dip in 2024 due to "integration fatigue," and a rebound in 2025 as reporting standards stabilize. Tan et al.'s bibliometric mapping confirms 2023–2025 as the most prolific period for DT×ESG research but notes that theoretical integration still lags behind empirical enumeration. Geographic concentration remains a key concern. Over 90% of the pooled studies rely on Chinese data, raising concerns about external validity, particularly for regions like Africa, Latin America, and Southeast Asia, where digital infrastructure, institutional quality, and ESG priorities differ. Some high-effect studies from Ghana (Celestin, 2024) and India (Gharia & Mogre, 2025) show that with the right mix of infrastructure and incentive alignment, emerging markets can also realize strong ESG gains, but further replication is needed to validate these findings in more contexts.

To integrate these patterns, an iterative DT–ESG loop consisting of three stages is proposed. Stage 1 (Resource Build-up) involves accumulating VRIN assets such as ERP kernels, cloud platforms, and AI systems. Stage 2 (Reconfiguration) reflects the Dynamic Capabilities engine, where firms sense regulatory and stakeholder signals, seize tools and opportunities, and reconfigure processes. Stage 3 (Stakeholder Judgment) introduces external validation investors, auditors, and consumers interpret ESG performance via digital disclosures, influencing subsequent digital investments. This loop explains why pilot-zone subsidies and regulatory certainty amplify ESG returns, while sluggish multi-sector bureaucracies struggle. It also aligns with Mendonça et al. (2025)'s lock-in critique: when ESG metrics are outdated or superficial, Stage 3 feedback cannot distinguish authentic innovation from symbolic compliance, stalling the feedback loop and limiting learning. Our proposed cycle helps explain not just what works, but when, where, and how providing a framework for understanding variance across firms and regions.

Despite accounting for known moderators, residual heterogeneity remains high. Our meta-regression reduces τ^2 by 39%, but 61% of the variance remains unexplained. Three primary sources likely contribute. First, measurement inconsistency: ESG is assessed using at least four distinct rating systems, and digital transformation is captured through dozens of proxies from web-scraped keyword counts to infrastructure spend to AI readiness indices. Second, policy divergence: China's Big-Data Pilot Zones offer incentives and mandates that are absent in many other countries, allowing for more structured DT–ESG pathways. Third, variation in firm size and absorptive capacity: our dataset spans from microenterprises to state-owned conglomerates. Smaller firms may be more agile but often lack the scale and financing to implement advanced technologies, while larger firms have infrastructure but may face bureaucratic inertia. These factors suggest the need for multi-level modeling in future research, ideally through hierarchical or meta-SEM designs that nest firm, industry, and country layers. Mendonça et al. (2025)'s call for tighter construct boundaries and Tan's proposal for a DESG taxonomy standardization remain highly relevant. Journals could accelerate this process by requiring standardized DT–ESG reporting templates, much like the health sciences use PRISMA or CONSORT to improve replicability and comparability.

Our findings suggest several key priorities for both firms and policymakers. First, firms should prioritize the sequencing of digital investments, embedding ESG metrics into operational workflows and data architectures before introducing complex tools like AI. Second, ethics and assurance should be integral to AI adoption, with explainability protocols and sector codes to mitigate governance risks. Third, incentive structures, such as tax credits or concessional loans, should be tied to verifiable digital disclosures.

This is particularly effective for SMEs, as shown in evidence from Uganda, where credit access magnified the eco-efficiency gains from integrated digital systems. Fourth, public investment is needed to extend these benefits to under-digitized regions and sectors. Governments and development agencies can play a catalytic role by co-funding broadband infrastructure, cloud platforms, and digital literacy programs that enable ESG progress beyond large firms and capital cities.

In conclusion, digital transformation is a powerful enabler of ESG performance, but its impact depends on both the type of technology and the context in which it's deployed. Core systems like ERP and cloud platforms deliver more consistent gains than advanced tools like AI, which require ethical guardrails and mature infrastructure. Our integrated RBV–Dynamic Capabilities–Stakeholder model helps explain how digital resources, adaptive capacity, and stakeholder evaluation work together to shape sustainability outcomes. Extending this cycle across sectors, geographies, and technologies can guide firms, regulators, and researchers toward digital investments that yield meaningful ESG impact where it matters most.

5.1. Practical implications

For executives and managers, the key takeaway is to approach digital transformation not as a collection of disconnected tech upgrades, but as a phased process that begins with what's already available and moves toward more advanced capabilities. Embedding ESG metrics into existing platforms like ERP systems, procurement portals, and workflow software ensures that key data, on energy use, safety incidents, or compliance violations, is collected and tracked from the source. This not only generates real-time, auditable data streams but also helps identify operational inefficiencies that can be corrected quickly, offering immediate returns. Firms that prioritize this foundational layer typically gain organizational trust and free up resources for more strategic upgrades. Once stable systems are in place, building a centralized cloud infrastructure ensures data quality, accessibility, and consistency across departments conditions that make the later addition of AI tools both more useful and less risky. Our findings show that firms which followed this progression delivered stronger environmental outcomes than those who rushed into AI deployments without upgrading their digital infrastructure.

Beyond the firm, capital-market actors, rating agencies, and supply-chain leaders also have a role to play. Investors and analysts should reward firms that provide machine-readable ESG disclosures via APIs or real-time dashboards, as these reduce information asymmetry and improve forecasting. Lenders can enhance risk assessments by factoring in DT readiness, such as the extent to which emissions data are sensor-based rather than self-reported. Auditors and ESG raters should develop simple, reliable protocols for evaluating AI tools focusing on data lineage, model bias, and drift detection to give boards the confidence to approve them. For smaller firms, particularly SMEs in emerging markets, cloud-based subscription tools offer a practical way to avoid the high upfront costs of on-premise infrastructure. Case studies from Uganda show that when these digital tools are paired with credit access and management training, SMEs achieve measurable gains in eco-efficiency. Framing these changes around SDG goals decent work (SDG 8), innovation (SDG 9), responsible consumption (SDG 12), and climate action (SDG 13) can also help firms align internal reforms with external expectations.

5.2. Theoretical implications

This study contributes to theory by highlighting the dual identity of digital assets under the RBV. On one hand, technologies like cloud platforms and ERP systems function as VRIN resources within the firm, boosting efficiency and coordination. On the other hand, these same tools act as external legitimacy signals when their use enables credible ESG reporting to stakeholders. This duality becomes meaningful only when firms reconfigure their digital tools in response to evolving expectations from regulators, investors, and customers. Recognizing this tension helps bridge long-standing divides between internal-capability theories like RBV and external-legitimacy theories rooted in institutionalism. Future research can explore how this dual nature changes over time whether digital tools shift from internal value drivers to external legitimacy levers depending on policy shocks, market shifts, or technological upgrades.

Additionally, the study calls for more fine-grained theorizing around digital transformation itself. Rather than treating DT as a single construct, scholars should distinguish between different layers of digital adoption transactional (e.g. process automation), integrative (e.g. cloud and data infrastructure), and cognitive (e.g. AI and analytics). Our findings suggest that operationally embedded tools tend to generate more stable ESG outcomes than cognitive tools like AI, which are more susceptible to opacity and auditability challenges. These tiers trigger different mediators cost efficiency, organizational learning, or strategic foresight and respond differently to boundary conditions such as regulatory scrutiny or firm size. Typology-sensitive models can better explain why the same digital investment produces divergent results across firms or industries. Furthermore, it was found that ESG returns are not static but depend heavily on contextual factors like digital maturity, sector pressure, and regulatory certainty. This underlines the need for contingency models that can nest firm-level routines within broader policy and supply-chain ecosystems. Future research might use meta-SEM or longitudinal designs to explore how these dynamics evolve over time.

5.3. Policy implications

For governments and development partners, the immediate policy priority is to support foundational digitization through targeted incentives. These might include tax credits, matching grants, or concessional loan guarantees, especially for SMEs and under-digitized sectors. Evidence shows that cloud-based ERP systems and ESG data platforms generate faster and more scalable sustainability improvements than hardware subsidies, particularly in low-resource settings. To avoid wasteful spending, eligibility criteria should be tied to verifiable, machine-readable disclosures rather than traditional CSR reports, and beneficiaries should be required to meet minimum cybersecurity standards. This approach ensures that firms not only adopt digital tools but use them to generate credible, actionable sustainability data.

Regulators should also align compliance demands with sectoral capacity. Imposing uniform reporting rules risks stalling progress among micro and small firms. Instead, a graduated approach, light-touch rules for SMEs and stricter timelines for large or listed firms can encourage broader participation. Policymakers also need to strengthen oversight of AI-based ESG tools. Boards need assurance protocols covering model explainability, data lineage, and drift detection, especially as AI use expands in governance functions. Regulatory sandboxes where firms, auditors, and watchdogs co-design these frameworks can speed up adoption while maintaining trust. Climate-related policies should reinforce digital accountability through incentives: for example, linking carbon trading rebates or green public procurement to verifiable digital traceability. Finally, governments should invest in building the ecosystem. Dedicated funding for ESG-tech research in developing countries can uncover region-specific barriers like poor broadband access or fragmented supply chains. Aligning digital-industrial strategies with the SDGs will help justify long-term investments in data infrastructure, vocational training, and innovation hubs, advancing both economic and sustainability goals in a coordinated, measurable way.

6. Limitations and future research

This meta-analysis offers meaningful insights into the digital transformation–ESG performance relationship, but some limitations must be acknowledged. A major constraint is geographic skew: over 90% of the studies included were based on Chinese firms. While this concentration benefits from consistent reporting standards and data availability, it limits the generalizability of results to other institutional, regulatory, and infrastructural contexts. Regions such as Sub-Saharan Africa, Southeast Asia, and Latin America operate under different technological constraints, policy priorities, and ESG reporting cultures. Future research should address this imbalance by drawing on emerging data platforms like Africa's ESG-Hub, India's MCA-21, or Brazil's CVM-B3 and incorporating mixed data types such as satellite imagery or sensor-based reporting where formal ESG disclosures are weak.

A second limitation is the lack of uniformity in how digital transformation and ESG performance are conceptualized and measured across studies. The use of diverse proxies ranging from ERP investments to

AI patent filings makes it difficult to disentangle which type of digital capability actually drives specific ESG outcomes. Similarly, ESG metrics vary widely, often conflating sustainability with CSR. Although a typology coding was used to minimize noise, high residual heterogeneity ($I^2 > 90\%$) indicates that construct inconsistency remains a serious issue. To advance the field, future studies should converge around layered DT frameworks distinguishing transactional, integrative, and cognitive systems and rely on standardized ESG indicators (e.g. GRI 302 for energy, SASB codes for data privacy or labor conditions). Methodologically, the field also needs to evolve beyond static correlation by adopting time-lagged regressions, panel meta-analysis, and dynamic structural models that can trace how DT–ESG links change over time.

Finally, publication bias and the fast-moving nature of digital technologies pose additional challenges. Funnel plots suggest possible small-study inflation, and the absence of published null results may inflate the perceived strength of DT–ESG links. Editors and funders should support replication studies and registered reports, particularly in underrepresented regions. Meanwhile, the definition of "digital" continues to evolve blockchain, digital twins, green AI, and federated learning are beginning to influence ESG strategies but are rarely captured in existing empirical datasets. Future work should develop reliable proxies for these emerging tools and adopt multi-level designs that reflect the complexity of real-world ESG systems from individual actors and organizational routines to national regulations and global standards. Only by addressing these gaps can researchers shift from broad generalizations to context-sensitive, actionable insights on when, how, and for whom digital transformation improves sustainability outcomes.

Acknowledgments

We sincerely acknowledge the support of Mbarara University of Science and Technology and the University of Doha for Science and Technology, whose access to academic resources and research databases made this work possible.

Author contributions

CRediT: **Dedrix Stephenson Bindeeba**: Conceptualization, Data curation, Formal analysis, Methodology, Writing – original draft, Writing – review & editing; **Eddy Kurobuza Tukamushaba**: Methodology, Supervision, Validation, Writing – review & editing; **Rennie Bakashaba**: Data curation, Methodology, Software, Validation, Writing – original draft.

Consent for publication

Not applicable. This study did not involve the publication of any identifiable individual data (e.g. images, videos, voice recordings, or personal details).

Disclosure statement

The authors declare that there are no competing interests or potential conflicts of interest related to the research, authorship, or publication of this article.

Funding

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

About the authors

Dedrix Stephenson Bindeeba is pursuing a PhD at the Faculty of Business and Management Sciences, Mbarara University of Science and Technology, Uganda. He holds an MBA in Big Data Management and a Master's degree in Monitoring and Evaluation. His doctoral work examines how digital transformation contributes to sustainable business models, with a particular focus on cleaner production, green entrepreneurship, and the role of human capital in advancing organizational sustainability.

Prof. Eddy Kurobuza Tukamushaba is Professor of Sustainable Tourism Management at the University of Doha for Science and Technology and serves as Chief Executive Officer of TIMEL Hospitality Consult Ltd, Uganda. His academic and professional expertise spans sustainable business management, digital transformation, the circular economy, and tourism management. He is widely published in leading journals and has received several best paper awards at international conferences. His current research agenda explores digitalization for sustainability, consumer behavior in responsible markets, and circular economy practices that build business resilience.

Dr. Rennie Bakashaba earned his PhD in Economics and an MSc in International Business and Finance. He is a Senior Lecturer at the Faculty of Business and Management Sciences, Mbarara University of Science and Technology. His scholarship centers on entrepreneurship, firm theory, SME development challenges, and the pathways to sustainable growth for small and medium enterprises in developing regions.

ORCID

Dedrix Stephenson Bindeeba http://orcid.org/0009-0001-8334-206X
Eddy Kurobuza Tukamushaba http://orcid.org/0000-0002-8110-6581
Rennie Bakashaba http://orcid.org/0009-0008-8310-402X

Data availability statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

References

Afum, E., Agyabeng-Mensah, Y., Baah, C., Acquah, I. S. K., & Osei, M. B. (2024). Empirical evidence of SMEs' ecopreneurship posture, green competitiveness and community-based performance: The neglected missing linkages of green practices. *International Journal of Emerging Markets*, *19*(10), 2691–2711. https://doi.org/10.1108/IJOEM-10-2021-1577

Al Halbusi, H., Al-Sulaiti, K. I., Alalwan, A. A., & Al-Busaidi, A. S. (2025). AI capability and green innovation impact on sustainable performance: Moderating role of big data and knowledge management. *Technological Forecasting and Social Change*, *210*, 123897. https://doi.org/10.1016/j.techfore.2024.123897

Asbeetah, Z., Alzubi, A., Khadem, A., & Iyiola, K. (2025). Harnessing digital transformation for sustainable performance: Exploring the mediating roles of green knowledge acquisition and innovation performance under digital transformational leadership. *Sustainability*, *17*(5), 2285. https://doi.org/10.3390/su17052285

Barney, J. B. (1991). Firm resources and sustained competitive advantage. *Journal of Management*, *17*(1), 99–120. https://doi.org/10.1177/014920639101700108

Begg, C. B., & Mazumdar, M. (1994). Operating characteristics of a rank correlation test for publication bias. *Biometrics*, *50*(4), 1088–1101. https://doi.org/10.2307/2533446

Bindeeba, D. S., Atuhaire, S., Bakashaba, R., & Tukamushaba, E. K. (2025a). Digital business process integration and sustainability among SMEs: The mediating role of operational efficiency and the moderating role of credit access. *Journal of Sustainable Business*, *10*(1), 11. https://doi.org/10.1186/s40991-025-00121-6

Bindeeba, D. S., Bakashaba, R., Tukamushaba, E. K., & Atuhaire, S. (2025b). From green HRM to sustainable business performance: A two-stage meta-analytic SEM of the mediating role of green innovation. In *Cogent Business and Management* (Vol. 12, Issue 1). Cogent OA. https://doi.org/10.1080/23311975.2025.2536678

Bindeeba, D. S., Tukamushaba, E. K., & Bakashaba, R. (2025c). Digital transformation and its multidimensional impact on sustainable business performance: Evidence from a meta-analytic review. *Future Business Journal*, *11*(1), 90. https://doi.org/10.1186/s43093-025-00511-z

Bindeeba, D. S., Tukamushaba, E. K., Bakashaba, R., & Atuhaire, S. (2025d). Green human resources management and green innovation: a meta-analytic review of strategic human resources levers for environmental sustainability. In *Discover Sustainability* (Vol. 6, Issue 1). Springer Nature. https://doi.org/10.1007/s43621-025-01444-x

Borenstein, M., Hedges, L. V., Higgins, J. P. T., & Rothstein, H. R. (2009). *Introduction to meta-analysis*. John Wiley & Sons. https://doi.org/10.1002/9780470743386 SCIRP

Borenstein, M., Hedges, L. V., Higgins, J. P. T., & Rothstein, H. R. (2011). *Meta-analysis with R*. John Wiley & Sons.

Celestin, M. (2024). Environmental, Social, and Governance (ESG) Accounting: Insights from Ghana-Based Corporations. https://www.researchgate.net/publication/390406779

Chen, D., & Wang, S. (2024). Digital transformation, innovation capabilities, and servitization as drivers of ESG performance in manufacturing SMEs. *Scientific Reports*, *14*(1), 24516. https://doi.org/10.1038/s41598-024-76416-8

Chen, L., Chen, Y., & Gao, Y. (2024). Digital transformation and ESG performance: A quasinatural experiment based on China's environmental protection law. *International Journal of Energy Research*, *2024*(1), 1–16. https://doi.org/10.1155/2024/8895846

Chen, Y., & Ren, J. (2025). How does digital transformation improve ESG performance? Empirical research from 396 enterprises. *International Entrepreneurship and Management Journal , 21*(27), 1–19. https://doi.org/10.1007/s11365-024-01011-2

Crona, B., Folke, C., & Galaz, V. (2021). The Anthropocene reality of financial risk. *One Earth*, *4*(5), 618–628. https://doi.org/10.1016/j.oneear.2021.04.016

Cui, J. (2025). The effect of human-AI collaboration and digitalization on green ESG performance: Empirical evidence from Chinese listed companies. https://doi.org/10.20944/preprints202504.0911.v1

Cui, J. (2025). The impact of financial technology innovation on ESG performance in Chinese multimedia enterprises. https://doi.org/10.13140/RG.2.2.12513.01120

Ding, X., Sheng, Z., Appolloni, A., Shahzad, M., & Han, S. (2024). Digital transformation, ESG practice, and total factor productivity. *Business Strategy and the Environment*, *33*(5), 4547–4561. https://doi.org/10.1002/bse.3718

Duval, S., & Tweedie, R. (2000). Trim and fill: A simple funnel-plot–based method of testing and adjusting for publication bias in meta-analysis. *Biometrics*, *56*(2), 455–463. PubMed https://doi.org/10.1111/j.0006-341x.2000.00455.x

Egger, M., Davey Smith, G., Schneider, M., & Minder, C. (1997). Bias in meta-analysis detected by a simple, graphical test. *BMJ (Clinical Research ed.)*, *315*(7109), 629–634. https://doi.org/10.1136/bmj.315.7109.629

Eriandani, R., & Winarno, W. A. (2023). ESG and firm performance: The role of digitalization. *Journal of Accounting and Investment*, *24*(3), 993–1010. https://doi.org/10.18196/jai.v24i3.20044

Freeman, R. E. (1984). *Strategic management: A stakeholder approach*. Pitman.

Fu, T., & Li, J. (2023). An empirical analysis of the impact of ESG on financial performance: The moderating role of digital transformation. *Frontiers in Environmental Science*, *11*, 1256052, 1–16. https://doi.org/10.3389/fenvs.2023.1256052

Geyskens, I., Steenkamp, J.-B. E. M., & Kumar, N. (1999). A meta-analysis of satisfaction in marketing channel relationships. *Journal of Marketing Research*, *36*(2), 223–238. SAGE Journals https://doi.org/10.1177/002224379903600207

Gharia, R., & Mogre, S. (2025). Digital transformation empowers ESG performance based on the mediating effect of green innovation.

Guo, X., & Pang, W. (2025). The impact of digital transformation on corporate ESG performance. *Finance Research Letters*, *72*, 106518. https://doi.org/10.1016/j.frl.2024.106518

He, X., & Chen, W. (2024). Digital transformation and environmental, social, and governance performance from a human capital perspective. *Sustainability*, *16*(11), 4737. https://doi.org/10.3390/su16114737

Hedges, L. V., & Vevea, J. L. (1998). Fixed- and random-effects models in meta-analysis. *Psychological Methods*, *3*(4), 486–504. Northwestern Scholars https://doi.org/10.1037/1082-989X.3.4.486

Hizarci-Payne, A. K., İpek, İ., & Kurt Gümüş, G. (2021). How environmental innovation influences firm performance: A meta-analytic review. *Business Strategy and the Environment*, *30*(2), 1174–1190. https://doi.org/10.1002/bse.2678

Hizarci-Payne, E., Smith, C., & Osei, R. (2021). The digital economy and sustainable development: A systematic review. *Journal of Cleaner Production*, *278*, 123807. https://doi.org/10.1016/j.jclepro.2020.123807

Hunter, J. E., & Schmidt, F. L. (2004). *Methods of meta-analysis: Correcting error and bias in research findings* (2nd ed.). SAGE.

Intergovernmental Panel on Climate Change. (2022). *Climate change 2022: Impacts, adaptation and vulnerability. Working Group II contribution to the Sixth Assessment Report of the IPCC* (H.-O. Pörtner et al., Eds.). Cambridge University Press. https://doi.org/10.1017/9781009325844ResearchGate.

Jing, H., & Zhang, S. (2024). The impact of artificial intelligence on ESG performance of manufacturing firms: The mediating role of ambidextrous green innovation. *Systems*, *12*(11), 499. https://doi.org/10.3390/systems12110499

Kalyani, S., & Mondal, R. (2024). Is ESG disclosure creating value propositions for the firms? An SLR and meta-analysis of how ESG affects the financials of a firm. *Corporate Ownership and Control*, *21*(1), 96–117. https://doi.org/10.22495/cocv21i1art9

Khan, I. S., Ahmad, M. O., & Majava, J. (2023). Industry 4.0 innovations and their implications: An evaluation from sustainable development perspective. *Journal of Cleaner Production*, *405*, 137006. https://doi.org/10.1016/j.jclepro.2023.137006

Kong, J., Goh, M., & Cao, Y. (2024). Can digital economy development facilitate corporate ESG performance? *Sustainability*, *16*(10), 3956. https://doi.org/10.3390/su16103956

Krippendorff, K. (2018). *Content analysis: An introduction to its methodology* (4th ed.). SAGE.

Kwilinski, A., Lyulyov, O., & Pimonenko, T. (2023). Unlocking sustainable value through digital transformation: An examination of ESG performance. *Information,)14*(8), 444. https://doi.org/10.3390/info14080444

Li, J., & Li, S. (2022). Environmental protection tax, corporate ESG performance, and green technological innovation. *Frontiers in Environmental Science*, *10*, 982132, 1–10. https://doi.org/10.3389/fenvs.2022.982132

Li, J., Wu, T., Hu, B., Pan, D., & Zhou, Y. (2025). Artificial intelligence and corporate ESG performance. *International Review of Financial Analysis*, *102*, 104036. https://doi.org/10.1016/j.irfa.2025.104036

Li, W., & Zhang, M. (2024). Digital transformation, absorptive capacity and enterprise ESG performance: A case study of strategic emerging industries. *Sustainability*, *16*(12), 5018. https://doi.org/10.3390/su16125018

Li, Y., Zheng, L., Xie, C., & Fang, J. (2024a). Big data development and enterprise ESG performance: Empirical evidence from China. *International Review of Economics & Finance*, *93*, 742–755. https://doi.org/10.1016/j.iref.2024.05.027

Li, Y., Zheng, Y., Li, X., & Mu, Z. (2024b). The impact of digital transformation on ESG performance. *International Review of Economics & Finance*, *96*, 103686. https://doi.org/10.1016/j.iref.2024.103686

Li, Z., & Li, M. (2025). Does environmental, social, and governance performance affect corporate green innovation? Evidence from China. *Polish Journal of Environmental Studies*, *34*(3), 2273–2283. https://doi.org/10.15244/pjoes/187600

Lipsey, M. W., & Wilson, D. B. (2001). *Practical meta-analysis*. SAGE.

Liu, H., & Jung, J. S. (2024). Impact of digital transformation on ESG management and corporate performance: Focusing on the empirical comparison between Korea and China. *Sustainability*, *16*(7), 2817. https://doi.org/10.3390/su16072817

Liu, Z., Pang, Y., & Pan, Y. (2025). Emerging market MNEs, digital transformation and ESG performance: Evidence from China's listed companies. *Applied Economics*, *57*(27), 3758–3775. https://doi.org/10.1080/00036846.2024.2337820

Lu, Y., Xu, C., Zhu, B., & Sun, Y. (2024). Digitalization transformation and ESG performance: Evidence from China. *Business Strategy and the Environment*, *33*(2), 352–368. https://doi.org/10.1002/bse.3494

Luo, Z. (2024). The impact of firm digital transformation on environmental, social, and governance performance: Evidence from China. *Economics*, *18*(1), 20220096, 1–12. https://doi.org/10.1515/econ-2022-0096

Mendonça, J. A., Roberto, F. R. A., Kai, D. A., & Benitez, G. B. (2025). The lock-in effect on ESG and business performance relationship: A Critical Examination and Meta-Analysis. In *Corporate Social Responsibility and Environmental Management*. John Wiley and Sons Ltd. https://doi.org/10.1002/csr.70062

Naderi, R., Ghorbani, S., & Khayati, F. (2022). Digital transformation and corporate sustainability: A systematic review and future research agenda. *Technological Forecasting and Social Change*, *180*, 121687. https://doi.org/10.1016/j.techfore.2022.121687 ResearchGate

Oduro, S. (2024). Eco-innovation and SMEs' sustainable performance: A meta-analysis. European Journal of Innovation Management, 27(9), 248–279. https://doi.org/10.1108/EJIM-11-2023-0961

Organisation for Economic Co-operation and Development (OECD). (2024). *Global corporate sustainability report 2024*. OECD Publishing. https://www.oecd.org/publications/global-corporate-sustainability-report-2024_8416b635-en.html

Orwin, R. G. (1983). A fail-safe N for effect size in meta-analysis. *Journal of Educational Statistics*, *8*(2), 157–159. wviechtb.github.io https://doi.org/10.3102/10769986008002157

Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., Shamseer, L., Tetzlaff, J. M., Akl, E. A., Brennan, S. E., Chou, R., Glanville, J., Grimshaw, J. M., Hróbjartsson, A., Lalu, M. M., Li, T., Loder, E. W., Mayo-Wilson, E., McDonald, S., … Moher, D. (2021). The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *Systematic Reviews*, *10*(1), *10*(1), 1–11. https://doi.org/10.1186/s13643-021-01626-4

Peterson, R. A., & Brown, S. P. (2005). On the use of beta coefficients in meta-analysis. *The Journal of Applied Psychology*, *90*(1), 175–181. PubMed https://doi.org/10.1037/0021-9010.90.1.175

Pham, T. N., Tran Hoang, M. T., Nguyen Tran, Y. N., & Nguyen Phan, B. A. (2024). Combining digitalization and sustainability: Unveiling the relationship of digital maturity degree, sustainable supply chain management practices and performance. *International Journal of Productivity and Performance Management*, *73*(8), 2508–2529. https://doi.org/10.1108/IJPPM-06-2023-0311

Pursiainen, V., Sun, H., Xiang, Y., Ceccarelli, M., Chen, S., Couvert, M., Döttling, R., Florackis, C., Gao, H., Gounopoulos, D., Huang, S., Lin, T.-C., Liu, X., Luu, E., Karmaziene, E., Kölbel, J., Von Meyerinck, F., Moreau, Q., Newton, D., … Zou, K. (2021). *Competitive Pressure and ESG** https://www.unilever.com/news/news-search/2021/no-trade-off-between-purpose-and-performance/

Qaiser, A., Ali, M., Fahad, M., Rafique, Z., & Batool, W. (2025). The critical review of social sciences studies the Nexus between artificial intelligence and ESG performance: A case from manufacturing firms of China. *The Critical Review of Social Sciences Studies*, *3*(1), 2052–2062. https://thecrsss.com/index.php/Journal/about

Raza, Z., & Woxenius, J. (2023). Customer-driven sustainable business practices and their relationships with environmental and business performance—Insights from the European shipping industry. *Business Strategy and the Environment*, *32*(8), 6138–6153. https://doi.org/10.1002/bse.3477

Ren, S., & Mohd Isa, S. (2023). The impact of digital transformation on corporate ESG performance: Empirical evidence from Chinese listed companies. *Journal of International Business, Economics and Entrepreneurship*, *8*(1), 6165, 1–23. https://doi.org/10.3390/su17136165

Robeco. (2023). Digitalization and sustainability: Robeco's perspective. Robeco Institutional Asset Management.

Rosenthal, R. (1979). The "file drawer problem" and tolerance for null results. *Psychological Bulletin*, *86*(3), 638–641. ResearchGate https://doi.org/10.1037/0033-2909.86.3.638

Sang, Y., Loganathan, K., & Lin, L. (2024). Digital transformation and firm ESG performance: The mediating role of corporate risk-taking and the moderating role of top management team. *Sustainability*, *16*(14), 5907. https://doi.org/10.3390/su16145907

Schmidt, F. L., & Hunter, J. E. (2014). *Methods of meta-analysis: Correcting error and bias in research findings* (3rd ed.). SAGE.

Su, X., Wang, S., & Li, F. (2023). The impact of digital transformation on ESG performance based on the mediating effect of dynamic capabilities. *Sustainability*,)*15*(18), 13506. https://doi.org/10.3390/su151813506

Sun, L., & Saat, N. A. M. (2023). How does intelligent manufacturing affect the ESG performance of manufacturing firms? Evidence from China. *Sustainability*,)*15*(4), 2898. https://doi.org/10.3390/su15042898

Tan, Q. L., Hashim, S., & Zheng, Z. (2025). Environmental Social Governance (ESG) in digitalization research: A bibliometric analysis. In *SAGE Open*. (Vol. 15, Issue 1). SAGE Publications Inc. https://doi.org/10.1177/21582440241310953

Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. *Strategic Management Journal*, *18*(7), 509–533. https://doi.org/10.1002/(SICI)1097-0266(199708)18:7<509::AID-SMJ882>3.0.CO;2-Z

United Nations Framework Convention on Climate Change. (2015). *Paris Agreement* https://unfccc.int/documents/184656

Wang, H., Jiao, S., Bu, K., Wang, Y., & Wang, Y. (2023). Digital transformation and manufacturing companies' ESG responsibility performance. *Finance Research Letters*, *58*, 104370. https://doi.org/10.1016/j.frl.2023.104370

Wang, J., Hong, Z., & Long, H. (2023). Digital transformation empowers ESG performance in the manufacturing industry: From ESG to DESG. *Sage Open*, *13*(4), 1–21. https://doi.org/10.1177/21582440231204158

Wang, L., & Hou, S. (2024). The impact of digital transformation and earnings management on ESG performance: Evidence from Chinese listed enterprises. *Scientific Reports*, *14*(1), 783. https://doi.org/10.1038/s41598-023-48636-x

Wang, M., & Zhang, D. (2024). Big data infrastructure and corporate ESG performance: Evidence from listed Chinese manufacturing companies. *Sustainability*, *16*(12), 5147. https://doi.org/10.3390/su16125147

Wang, S. (2025). The impact of digital transformation of enterprises on ESG performance, 13.

Wang, Y., & Wang, D. D. (2025). The dual path of the impact of digital technology adoption on ESG performance. *Sustainability*, *17*(6), 2341. https://doi.org/10.3390/su17062341

Wu, X., Li, L., Liu, D., & Li, Q. (2024). Technology empowerment: Digital transformation and enterprise ESG performance-Evidence from China's manufacturing sector. *PloS One*, *19*(4), e0302029. April). https://doi.org/10.1371/journal.pone.0302029

Wu, Y. (2024). The impact of digital technology innovation on ESG performance: Evidence from A-share listed companies in China. SHS Web of Conferences, 207, 01021. https://doi.org/10.1051/shsconf/202420701021

Xie, H., & Wu, F. (2025). Artificial intelligence technology and corporate ESG performance: Empirical evidence from Chinese-listed firms. *Sustainability*,)*17*(2), 420. https://doi.org/10.3390/su17020420

Xie, X., Zhu, H., & Zhao, J. (2024). How effective is digital transformation? Heterogeneous insights from listed companies' ESG performance. *Humanities and Social Sciences Communications*, *11*(1), 1534. https://doi.org/10.1057/s41599-024-04039-5

Yang, P., Hao, X., Wang, L., Zhang, S., & Yang, L. (2024). Moving toward sustainable development: The influence of digital transformation on corporate ESG performance. *Kybernetes*, *53*(2), 669–687. https://doi.org/10.1108/K-03-2023-0521

Yang, Y., & Han, J. (2023). Digital transformation, financing constraints, and corporate environmental, social, and governance performance. *Corporate Social Responsibility and Environmental Management*, *30*(6), 3189–3202. https://doi.org/10.1002/csr.2546

Yu, G. (2025). Digital transformation, human capital upgrading, and enterprise ESG performance: Evidence from Chinese listed enterprises. *Oeconomia Copernicana*, *15*(4), 1465–1508. https://doi.org/10.24136/oc.3058

Yu, J., & Hwang, Y. S. (2024). The interaction effects of board independence and digital transformation on environmental, social, and governance performance: Complementary or substitutive? *Sustainability*,)*16*(20), 9098. https://doi.org/10.3390/su16209098

Yusof, N., Tabassi, A. A., & Kamal, E. M. (2020). Do environmental, economic and reputational advantages strengthen green practices' impact on environmental performance? *Corporate Social Responsibility and Environmental Management*, *27*(5), 2081–2093. https://doi.org/10.1002/csr.1948

Zhang, Z. (2024). Can energy internet improve corporate ESG performance?–Evidence from Chinese high energy-consuming companies. *Heliyon*, *10*(2), e24175. https://doi.org/10.1016/j.heliyon.2024.e24175

Zhao, F., Han, Z., & Wang, L. (2024). Digitization path to improve ESG performance: A study on organizational perspectives. *PloS One*, *19*(12), e0313686. https://doi.org/10.1371/journal.pone.0313686

Zhao, Q., Li, X., & Li, S. (2023). Analyzing the relationship between digital transformation strategy and ESG performance in large manufacturing enterprises: The mediating role of green innovation. *Sustainability*,)*15*(13), 9998. https://doi.org/10.3390/su15139998

Zhao, Y., Zhang, C., Zhao, Y., & Zhou, L. (2025). Data-driven sustainability: Examining the impact of data element utilization on corporate ESG performance. *Finance Research Letters*, *73*, 106673. https://doi.org/10.1016/j.frl.2024.106673

Zheng, X., & Bu, Q. (2024). Enterprise ESG performance, digital transformation, and firm performance: Evidence from China. *Sage Open*, *14*(4), 1–25. https://doi.org/10.1177/21582440241291680

Zhu, Y., & Jin, S. (2023). How does the digital transformation of banks improve efficiency and environmental, social, and governance performance? *Systems*, *11*(7), 328. https://doi.org/10.3390/systems11070328