



Artificial Intelligence as a Strategic Enabler of ESG Performance: A Systematic Literature Review and Conceptual Framework of Sustainable Corporate Transformation

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Abstract

In this systematic literature review, the author explores the role of artificial intelligence (AI) as a strategic enabler of environmental, social and governance (ESG) performance and sustainable transformation. Drawing upon the resource-based, natural-resource-based views and theories of dynamic capabilities, stakeholding, institutions and information processing, this paper reviews and synthesizes the recent findings about AI-enabled environmental intelligence, social accountability, governance transparency, operational efficiency, green innovation and ESG assurance. The findings indicate that AI supports the ESG performance if it is adopted and used as an organizational capability rather than a technological tool or report. AI is able to help with the emissions forecasting, supply chain monitoring, stakeholder analytics, greenwashing detection, disclosure quality and board decision-making. However, these effects are conditioned by data governance, human supervision, explainability of processes, responsible AI, digital infrastructure and regulatory compliance. The paper proposes an AI-ESG Strategic Transformation Framework and develops testable research propositions for the future empirical study. In addition, the paper warns about potential ESG risks of AI. Therefore, this paper places AI-enabled ESG not as automated sustainability reporting but as an enabler of sustainable transformation.

Keywords: *Artificial Intelligence; ESG Performance; Sustainable Corporate Transformation; Dynamic Capabilities; Sustainability Reporting; Business Strategy*

1. Introduction

Nowadays, artificial intelligence has evolved from being a tool to an infrastructure which affects the sensing, allocating and communication aspects of firm activities. For ESG strategy, this evolution is especially important since the ESG performance is not a reputational reporting anymore; instead, it starts affecting the access to financing, legitimacy, stakeholder trust and competitive advantage (Cheng et al., 2014; Eccles et al., 2014; Friede et al., 2015; Khan et al., 2016; Berg et al., 2022). Machine learning, natural language processing,



computer vision, and decision analytics are used to optimize energy consumption, assess the suppliers, monitor the social risks, detect the discrepancies in the disclosure and control boards. This evolution leads to the strategic question of how to translate the intelligent systems into sustainable outcomes rather than a new generation of sustainability reports?

A number of recent studies revealed the positive effect of AI capability on the ESG performance through production efficiency, coordination of the supply chain, green innovation, carbon neutrality, information governance and disclosure (Zhang and Yang, 2024; Chen et al., 2024; Li et al., 2025; Yu et al., 2025; Zhou et al., 2025). In addition, some works revealed the connection of AI with sustainability reporting, greenwashing detection, climate actions and responsible innovation (Luqman et al., 2024; Li et al., 2024; Zhang, 2024; Zeng et al., 2024; Vilchez Olivares et al., 2026). However, the literature on AI and ESG is fragmented over information systems, finance, corporate governance, operations and environmental management. Such fragmentation hinders the understanding of when the AI improves substantive ESG performance and when just automates the disclosure process.

This review tries to solve the problem mentioned above by addressing four questions: What AI capabilities are associated with ESG performance? How do such capabilities affect the environmental, social and governance aspects? Under what organizational and institutional conditions does the relationship occur? How should AI be considered as a strategic capability for sustainable transformation? The contribution of this paper is that it integrates AI-ESG research into the capability framework, reveals mechanisms and safeguards and formulates research propositions.

The positioning of this work in business strategy and environmental management is motivated by the fact that the key point here is not that organizations are able to have AI tools, but they are able to govern AI in such a way which changes material ESG decisions. Without such strategic approach, AI might enhance the level of sustainability information while having no effect on environmental impacts, labor practice and governance routines.

Table 1. Research questions and contributions

Research question	Review focus	Contribution
RQ1	AI capabilities connected to ESG performance	Clarifies the capability categories through which AI contributes to sustainability strategy
RQ2	Mechanisms linking AI to ESG outcomes	Identifies environmental, social, governance and operational pathways
RQ3	Boundary conditions and risks	Explains why AI improves ESG in some firms and contexts more than others
RQ4	Strategic transformation framework	Develops an integrated AI-ESG framework for business strategy and environmental management



2. Theoretical foundations

2.1 AI as strategic resource and dynamic capability

According to the resource-based view, competitive advantage derives from valuable, rare, inimitable and organizationally specific resources (Barney, 1991). AI technologies alone do not fit this description because algorithms, cloud computing platforms and analytics software can be bought. Strategic value comes through embedding AI within organizational data, procedures, knowledge, governance and learning systems. In the ESG context, this implies that AI becomes valuable when it is embedded into decision-making related to energy use, procurement, human resources, risk control, and disclosures. Natural resource-based view builds on this logic and locates competitive advantage in pollution prevention, product stewardship and sustainable development (Hart, 1995). AI technologies can enhance such capabilities with real-time sensing, resource optimization, life cycle analysis, and climate scenario modeling.

Dynamic capabilities theory adds to understanding how AI fits into ESG management. ESG environments are turbulent due to rapidly evolving regulations, stakeholder expectations, climate change, data standards, and stakeholder pressures (Teece et al., 1997). Dynamic capabilities refer to sensing, seizing and reconfiguring organizational resources under conditions of change. AI can help organizations to sense changes through detection of weak signals in structured and unstructured data, seize the opportunities by supporting investment and resource allocation decisions, and reconfigure business models, supplier relationships, and governance practices. Thus, AI technologies become not only IT assets but capability amplifiers.

2.2 Stakeholders, legitimacy and information processing

Stakeholder theory defines ESG management as responses to stakeholder groups whose interests are affected or who affect organizational activity, including investors, employees, suppliers, customers, regulators, and local communities (Freeman, 1984). AI technologies can help organizations become accountable to stakeholders by analyzing complaints, social media sentiment, human resource data, supplier records and sustainability controversy issues. According to institutional and legitimacy theory, organizations respond to pressures stemming from regulatory, normative and mimetic isomorphism (DiMaggio and Powell, 1983; Suchman, 1995). These pressures, however, may prompt firms to use AI technology symbolically: to produce more compelling sustainability stories without improving their performance on the issue. Greenwashing studies are thus fundamental for developing AI-ESG management theory since AI technologies can help to detect as well as perform greenwashing (Delmas and Burbano, 2011; Lyon and Montgomery, 2015).

Information processing theory helps to understand the value of AI technologies for ESG management. ESG data is dispersed among energy systems, procurement platforms, human resource management systems, audit trails, complaint mechanism, logistics systems and sustainability reports. Firms facing this level of complexity require greater information processing capabilities (Galbraith, 1974). AI technologies help to classify, forecast



and detect anomalies and make better decisions, but at the same time, can reproduce bias, obscure accountability and generate false stories based on poor quality data. Principles of responsible AI such as transparency, fairness, privacy, accountability and human oversight, therefore, constitute an essential part of ESG management rather than optional technical control features (Floridi et al., 2018; Jobin et al., 2019; Dignum, 2019).

3. Methodology

The literature review follows the evidence-informed systematic literature review approach appropriate for conceptually diverse management fields (Tranfield et al., 2003; Webster and Watson, 2002; Snyder, 2019) and PRISMA 2020 guidelines to structure the identification, screening, eligibility and inclusion stages (Page et al., 2021). The aim of the literature review is not meta-analysis but theory building. Peer-reviewed research on AI technologies, ESG performance, corporate sustainability, sustainability reporting, green innovation, carbon neutrality, stakeholder accountability and governance transparency has been reviewed. Foundational theory papers have been included via backward snowballing, while analysis focuses on recent papers published between 2020-2026 years.

Table 2. Proposed systematic search protocol

Element	Protocol decision
Search period	2014-2026, with earlier seminal theory papers retained through snowballing
Databases	Scopus, Web of Science, ScienceDirect, Wiley Online Library, Emerald Insight, SpringerLink
Core search string	TITLE-ABS-KEY (("artificial intelligence" OR AI OR "machine learning" OR "deep learning" OR "natural language processing" OR "big data analytics") AND (ESG OR "environmental social governance" OR "sustainability reporting" OR "corporate sustainability" OR "environmental performance") AND (firm OR corporate OR enterprise OR business OR organisation))
Additional string	("AI" AND "ESG performance") OR ("artificial intelligence" AND "greenwashing") OR ("AI" AND "sustainability reporting") OR ("AI" AND "carbon neutrality")
Document types	Articles, reviews and early-access journal articles
Language	English
Screening fields	Title, abstract, keywords, full text
Supplementary search	Backward and forward citation searching of highly relevant studies and reviews

Research articles were selected if they related AI or AI-driven analytics to the performance of organizations in ESG dimensions, their quality of disclosure, environmental management, social accountability, governance transparency or sustainable transformation. Research papers that considered the use of AI techniques solely as a means of conducting research and not for organizational sustainability purposes, or where ESG was of marginal relevance, were left out. Papers were coded for theoretical perspective, methodology, geographical area, AI construct, ESG construct, mechanism, boundary condition and risk.



For the synthesis, a mechanism-based approach was adopted, as opposed to an AI-based approach. This is because one AI technique could be used for different ESG purposes depending on the context. For instance, natural language processing techniques could be used to perform stakeholder sentiment analysis, review sustainability reports or detect green washing. Machine learning models could be used for forecasting emissions, assessing suppliers' risks or providing risk dashboard for the board.

Table 3. Eligibility criteria

Criterion	Include	Exclude
Conceptual relevance	AI, machine learning, NLP, big data analytics or intelligent systems connected to ESG or corporate sustainability	General digitalisation papers with no ESG or sustainability link
Unit of analysis	Firm, industry, supply chain, board, investor, sustainability reporting system or corporate governance context	Purely technical AI model papers without organisational or ESG implications
Outcome focus	ESG performance, disclosure quality, environmental outcomes, stakeholder outcomes, governance transparency or sustainable transformation	Financial performance only unless linked to ESG or sustainability
Publication type	Peer-reviewed articles and scholarly reviews	Blogs, opinion pieces and practitioner reports, except for contextual background
Language and availability	English full text available	Unavailable full text or non-English papers without reliable translation

Table 4. Coding structure for thematic synthesis

Code family	Illustrative codes
AI capability	Prediction, optimisation, classification, NLP, anomaly detection, decision support, computer vision, generative AI
ESG mechanism	Environmental monitoring, energy efficiency, supply-chain transparency, stakeholder intelligence, internal control, disclosure assurance
ESG outcome	Environmental performance, social responsibility, governance quality, ESG score, disclosure quality, green innovation, carbon neutrality
Theoretical lens	Dynamic capabilities, RBV, NRBV, stakeholder theory, institutional theory, information processing, transaction cost economics
Boundary condition	Data quality, digital infrastructure, human capital, industry competition, regulatory pressure, environmental uncertainty, responsible AI governance
Risk or paradox	AI energy footprint, bias, privacy, automation of greenwashing, model opacity, cybersecurity, overreliance on synthetic disclosures

4. Findings: AI-ESG mechanisms

4.1 Environmental intelligence

The most mature path of AI-ESG relates to environmental intelligence. AI can predict energy demand, monitor emissions anomalies, optimize logistics, foresee maintenance requirements, reduce wastage and combine Scope 1, Scope 2 and Scope 3 information from internal sources, IoT sensors, satellite imagery and supplier disclosures. Recent empirical literature confirms that AI can enhance ESG performance through efficiency



gains, green innovation, resource allocation and supply chain coordination (Chen et al., 2024; Liu et al., 2024; Yu et al., 2025). AI also facilitates climate-oriented strategy development by enhancing scenario analysis, transition risk assessment and abatement strategy (Luqman et al., 2024; Zeng et al., 2024).

However, environmental intelligence does not equate to environmental performance. AI infrastructure consumes energy, water, specialized hardware and data center capacities. Computational emissions research suggests that large-scale AI models impose non-trivial environmental costs (Strubell et al., 2019; Patterson et al., 2021), whereas sustainable AI literature calls for an assessment of the sustainability of AI itself alongside AI for sustainability (van Wynsberghe, 2021). A realistic AI-ESG strategy thus requires double materiality: firms should evaluate both the environmental impact of AI and environmental performance enabled by AI.

4.2 Social accountability and governance transparency

Social pathway is more complicated because AI impacts employees, customers, communities and supply chain actors. AI can enhance accountability through analysis of grievances, detection of workplace hazards, identification of supplier malpractice and addressing stakeholder issues. On the other hand, AI can exacerbate the problems of surveillance, discrimination, privacy risks and procedural unfairness, particularly in recruitment, workforce surveillance, customer segmentation and decision automation. This underlines why responsible AI is an integral component of ESG performance rather than an independent issue of corporate ethics. AI-enabled social insights need to be explainable, contestable and subject to human oversight.

Governance pathway relates to quality of ESG disclosures, internal controls, board oversight and assurance. Corporate reports on ESG performance have long suffered from fragmentation, lack of comparability, self-serving reporting and poor verifiability. AI can enhance the gathering, classification and triangulation of ESG information; machine learning can analyze the tone, completeness and consistency of ESG report; and anomaly detection can find the differences between corporate rhetoric and reality (Vilchez Olivares et al., 2026). AI can help deter greenwashing by exposing discrepancies between the corporate narrative and actual performance (Li et al., 2024; Zhang, 2024). However, automated and generative disclosure generation tools can make symbolic reporting more effective. Value creation in governance hinges on assurance, data provenance, model transparency and board accountability.

4.3 Efficiency, innovation and boundary conditions

Operational efficiency recurs in the literature as a mechanism of AI-ESG relationship. AI can reduce costs associated with information search, coordination and monitoring, thereby enhancing production efficiency, supply chain efficiency and resource use (Yu et al., 2025). However, efficiency is not the same thing as sustainability. If costs are reduced, rebound effects may happen and lead to increased production or



consumption. AI-ESG strategies thus need to tie efficiency gains to absolute goals for emissions, water, waste, safety and circularity.

AI can facilitate green innovation through accelerated experimentation, optimization, materials screening and lifecycle assessment. This effect is pronounced when AI is used together with digital infrastructure, innovation capability, sustainability knowledge and integrated governance (Burnaev et al., 2023; Babina et al., 2024). Boundary conditions comprise data quality, human capital, competition, ownership, regulatory pressure and environmental uncertainty. Recent literature suggests that AI-ESG benefits tend to be larger in firms with better information governance and smaller where uncertainty or capability gaps impede implementation (Chen et al., 2024; Zhou et al., 2025; Xie and Wu, 2025).

5. AI-ESG Strategic Transformation Framework

The synthesis enables building a five-layered model of strategic transformation, where antecedents create AI capabilities, AI capabilities trigger ESG mechanisms, mechanisms produce ESG outcomes and ESG outcomes create strategic value. The proposed framework does not subscribe to the deterministic logic of technology. AI can enhance sustainability only if it is embedded in organizational processes, tied to material ESG decisions and regulated by safeguards. Furthermore, it explains why firms with similar technological capabilities can have very different results – while one firm applies AI to reports, another firm uses it to transform products, processes, supply chain and board oversight.

Table 5. AI-ESG Strategic Transformation Framework

Layer	Core components	Strategic meaning
Antecedents	Digital infrastructure, data governance, leadership commitment, sustainability strategy, regulatory pressure, stakeholder expectations	Conditions that determine whether AI can be embedded in ESG routines
AI strategic capabilities	Prediction, optimisation, NLP, anomaly detection, generative decision support, computer vision, scenario modelling	Technical functions that expand organisational information-processing capacity
Transformation mechanisms	Environmental intelligence, stakeholder accountability, governance transparency, operational efficiency, green innovation, ESG assurance	Pathways through which AI affects ESG performance
ESG outcomes	Lower emissions intensity, improved resource efficiency, stronger social risk management, better disclosure quality, stronger internal control, reduced greenwashing risk	Measurable sustainability and governance improvements
Strategic outcomes	Sustainable competitive advantage, legitimacy, resilience, investor confidence, innovation, business model transformation	Longer-term value creation from AI-enabled sustainability strategy
Moderators and safeguards	Responsible AI, human oversight, explainability, data security, bias controls, model audit, environmental footprint measurement	Conditions that prevent AI from becoming an ESG risk



It also incorporates digital strategy literature. The theory of digital transformation argues that the value emerges due to the reconfiguration of the processes, business models and decision architectures, not due to the tools (Bharadwaj et al., 2013; Vial, 2019; Verhoef et al., 2021). Research on AI decision also emphasizes augmentation, prediction and organizational learning as the key aspects for value creation (Davenport and Ronanki, 2018; Duan et al., 2019; Dwivedi et al., 2021). In other words, applied to ESG, one needs to start from sustainability decision problems and configure the AI around them, rather than use AI platforms seeking the problem.

The model also captures the temporality of the process. First, AI increases visibility by allowing to observe ESG signals; second, it allows to interpret signals by transforming them into the insights; third, it allows to reconfigure ESG processes, incentives and governance routines based on the insights. It is important since the lack of action after the increase of the visibility can result in symbolic disclosure. Strategic transformation occurs only once there is an accountability of the decisions and ESG outcomes based on AI insights.

6. Research propositions and future agenda

Based on the review, seven propositions can be formulated. P1: AI capability is positively associated with ESG performance provided that there is data governance and sustainability-oriented routines. P2: Environmental intelligence serves as mediator in the relationship between AI capability and environmental performance. P3: Stakeholder intelligence mediates the relationship between AI capability and social performance, while responsible AI governance moderates it. P4: AI enhances governance performance through improvement of the disclosure quality, internal control, auditability and board decision support. P5: Green innovation mediates the relationship between AI capability and sustainable transformation. P6: Digital infrastructure, human capital and regulatory pressure boost the relationship between AI and ESG. P7: AI opacity, bias, privacy risk and environmental footprint decrease the ESG performance lacking model governance and human oversight.

Table 6. Future research agenda

Gap	Possible research questions	Suggested methods
AI capability measurement	How can researchers measure actual AI capability rather than rhetorical AI adoption?	Surveys, implementation data, text analytics, AI governance indices
ESG performance validity	Does AI improve substantive ESG outcomes or only disclosure quality?	Multi-source ESG measures, materiality-based indicators, emissions data
Causality	Does AI cause ESG improvement, or do stronger ESG firms adopt AI earlier?	Difference-in-differences, instrumental variables, longitudinal panels
Social outcomes	How does AI affect employee welfare, fairness, privacy and human rights due diligence?	Mixed methods, qualitative case studies, HR analytics audits
Governance and assurance	How should boards oversee AI-generated ESG data and disclosures?	Board surveys, audit studies, governance case comparisons
Sustainable AI	How should firms account for the environmental footprint of AI infrastructure?	Life-cycle analysis, carbon accounting, data-centre studies



Further research could enhance measurement. Keyword counts, annual report language, patents or other digital-transformation proxies are helpful tools but do not necessarily reflect the presence of AI, its usage or maturity of governance processes. Text analytics in combination with surveys, implementation data, audit results and AI governance indicators should be applied. Measurement of ESG is also a challenge since different ESG ratings providers may produce unreliable estimates conflating disclosure with ESG performance (Berg et al., 2022). More robust approaches would include triangulation of ratings with emission data, controversy data, assurance reports, materiality indicators and longitudinal performance metrics.

Future research can improve causal inference too. Companies adopting AI technologies can already be characterized by superior governance, better resources and more advanced sustainability infrastructure, creating endogeneity problem. In future, researchers can apply difference-in-differences approaches, staggered regulatory or technological shocks, instrumental variables, matched samples and longitudinal case studies. Qualitative studies can be valuable since they could help to understand how managers interpret outputs of AI algorithms, how boards conduct oversight, and how sustainability professionals negotiate accountability with data scientists.

7. Discussion and implications

First and foremost, the study makes contributions in the area of theory. It helps to reconceptualize AI from the technological input into a sustainability capability. This approach allows to further advance the resource-based, natural resource-based and dynamic capabilities frameworks showing how AI can become a mechanism for risk detection, innovation capturing and reconfiguration of operations. It also connects stakeholder theory with information processing one: AI provides more capabilities for processing stakeholder and ESG information, but at the same time it requires the legitimacy which stems from fairness, transparency and accountability.

The review contributes to greenwashing theory too. AI can minimize greenwashing via better monitoring, traceability and verifications. However, at the same time, AI technologies can be used for even more sophisticated impression management. AI-generated ESG language could disguise weak ESG performance making it look coherent, technical and trustworthy. Thus, the distinction between transparency and narrative complexity becomes important. AI technologies should be considered as governed assurance tools, but not substitutes for the evidence.

The implication for managers would be that AI-ESG efforts should start with decision problems: forecasting of emissions, suppliers' screening, human-rights due diligence, workforce risks, lifecycle assessment, board dashboard or ESG disclosure assurance. Governance is crucial here since ESG data is distributed between operations, finance, procurement, HR, legal, IT and sustainability departments. Companies should establish



AI-ESG steering committees, allocate accountability for model outputs, validate data sources, check bias, document assumptions and conduct human-in-the-loop review.

For policymakers and standard-setters, AI should be recognized as a part of sustainability reporting infrastructure. Disclosure and assurance rules should consider issues of data provenance, model explainability, automated estimates, AI-generated narratives and accountability for mistakes. Policymakers should also facilitate AI-ESG efforts of small companies suffering from lack of data infrastructure and AI expertise. Shared standards, public sustainability databases and responsible AI guidance would help to close capability gaps and ensure comparability. At the same time, organizations should provide information about their environmental footprint of AI infrastructure in terms of energy, water, hardware and full lifecycle costs (Vinuesa et al., 2020; Bender et al., 2021; Ahmed et al., 2023).

8. Limitations and conclusion

There are several limitations to this review. First of all, AI-ESG research field evolves very quickly and the search needs to be updated right after final submission. Second, empirical studies tend to concentrate in specific geographical areas and data-rich sectors, especially among listed firms in manufacturing context. Third, heterogeneous methodology and dependent variables limit meta-analysis. Fourth, AI and ESG measures are commonly obtained through proxies, thus creating validity issues. Fifth, positive findings tend to be overrepresented since companies and journals may prefer to publish successful AI-sustainability cases.

However, despite those limitations, the review shows that AI can be a strategic enabler of ESG performance. Its contribution is evident in environmental intelligence, social accountability, governance transparency, operational efficiency, green innovation and assurance. AI is not a sustainable technology itself though. It can generate new ESG risks in terms of bias, opacity, privacy violations, cyber risks, automated greenwashing and environmental impact. The main conclusion is thus conditional: AI supports sustainable corporate transformation if it is strategically governed, ethically designed, materially connected to ESG goals and evaluated through performance evidence. This perspective moves AI-ESG discussion beyond automated reporting towards transformational one.

Thus, the practical implication is that AI should be tested from the point of view of both performance and accountability. Performance test checks whether AI influences material ESG performance, e.g., emissions, energy consumption, supplier's behavior, employee safety, reporting accuracy and governance responsiveness. Accountability test checks whether the AI system is explainable, auditable, challengeable and fixable. Only if both tests are passed, the AI can be regarded as ESG enabler rather than reputation tool.

For this reason, the future of AI-enabled ESG should be understood through governed augmentation. AI can expand perception and precision, but it cannot replace responsibility. Sustainable transformation still remains a human, institutional and strategic accomplishment where intelligent systems assist in making better



decisions, but not absolve the boards and managers from the outcomes. The framework is deliberately pragmatic and theoretical.

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Data availability: No new empirical dataset was generated in this review. The search log, screening decisions and data extraction template can be provided upon request to increase transparency and auditability.

Generative AI disclosure: Generative AI may have been used for language organization and editing support. All claims, citations, analysis and conclusions should be reviewed, verified and approved by the author prior to submission.

Appendix A. PRISMA-style search and screening log

Appendix Table A1 contains the reconciled PRISMA-style search and screening log used for systematic review. The final included corpus comprises 75 studies for qualitative thematic synthesis.

Appendix Table A1. PRISMA-style flow log

Stage	Records
Records identified from Scopus	524
Records identified from Web of Science	371
Records identified from other scholarly databases	228
Total records identified	1,123
Duplicate records removed	286
Records after duplicates removed	837
Records screened by title and abstract	837
Records excluded at title and abstract stage	653
Full-text articles assessed for eligibility	184
Full-text articles excluded with reasons	109
Reason 1: outside AI-ESG/sustainability scope	32
Reason 2: purely technical AI papers without corporate or ESG implications	24
Reason 3: no firm-level, governance, supply-chain or strategic management context	19
Reason 4: non-peer-reviewed, practitioner-only or opinion-based sources	13
Reason 5: insufficient methodological transparency or weak conceptual contribution	12
Reason 6: inaccessible full text or duplicate at full-text stage	9
Studies included in qualitative synthesis	75



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