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ARTICLE

AI-Driven Transformation of Environmental, Social, and Governance (ESG): A Systematic Review, Gap Analysis, and Future Research Agenda

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Abstract

Environmental, Social, and Governance (ESG) considerations have become a central framework for corporate accountability, regulatory compliance, and sustainable value creation amid growing environmental challenges, stakeholder expectations, and institutional pressures. At the same time, advances in Artificial Intelligence (AI) are transforming ESG systems by enabling large-scale data integration, predictive sustainability analytics, automated reporting, and real-time governance intelligence. These developments are accelerating the digitalization of sustainability management and reshaping how organizations measure, disclose, and govern ESG performance.

This study conducts a systematic literature review to synthesize and critically evaluate the emerging body of research on AI-driven ESG transformation. Adopting a socio-technical governance perspective, the review conceptualizes AI-enabled ESG integration as a transformative process in which algorithmic systems increasingly influence sustainability assessment, disclosure, monitoring, and decision-making across organizational and institutional contexts. The findings reveal that despite significant technological progress, several barriers continue to constrain the effective application of AI in ESG. These include fragmented and inconsistent ESG data infrastructures, algorithmic bias and opacity, regulatory fragmentation, weak explainability and auditability mechanisms, and unresolved ethical, social, and environmental risks. The review also identifies important gaps related to cross-country regulatory evidence, lifecycle assessments of AI technologies, stakeholder trust, and mechanisms for enhancing ESG disclosure credibility while mitigating greenwashing and machine-washing risks.

Based on these findings, the study proposes a future research agenda emphasizing ESG data standardization, trustworthy and explainable AI, regulatory harmonization, governance integration, and interdisciplinary approaches to understanding the broader sustainability implications of AI-enabled ESG systems.

Keywords: ESG; Artificial Intelligence; Sustainability Governance; Socio-Technical Systems; Responsible AI; ESG Disclosure; Digital Transformation.

1. INTRODUCTION

Environmental, Social, and Governance (ESG) performance has emerged as a foundational construct for assessing corporate sustainability, systemic risk exposure, and long-term value creation. Concurrently, accelerating digital transformation---particularly in emerging economies---has reconfigured industrial competitiveness, especially within manufacturing sectors central to national development. As a result, firms are increasingly required to move beyond efficiency-based metrics toward multidimensional evaluation systems that embed ESG accountability as a core legitimacy, valuation, and governance criterion [1]. This reflects a structural institutional transition in which sustainability is embedded within corporate performance systems and stakeholder governance regimes [2,3].

Artificial Intelligence (AI) is widely recognized as a general-purpose technology with transformative implications for organizational and industrial systems. It enhances decision efficiency, operational productivity, and cost optimization, while accelerating enterprise-wide digital transformation [4,5]. At the organizational level, AI has evolved from a peripheral governance concern to a central mechanism of managerial decision-making [6], with firms increasingly acting as co-developers of AI-enabled systems. This evolution positions AI as an embedded socio-technical capability that reshapes governance architectures, decision logics, and value creation structures [7,8].

Beyond organizational boundaries, AI operates as a general-purpose technology with applications across finance [9], healthcare [10], agriculture [11], and manufacturing [12]. In production systems, AI enables digitization, autonomous control, and optimized resource allocation [13], thereby improving operational efficiency and system performance. Collectively, these developments reinforce AI's systemic role in reshaping industrial structures and organizational capabilities [14].

1.1. AI Integration in ESG Systems

Within ESG contexts, AI adoption initially focused on operational efficiency, particularly production optimization and supply chain coordination [15,16]. However, its role has progressively expanded toward ESG-specific governance functions, including real-time environmental monitoring, automated sustainability reporting, and predictive ESG risk analytics [17,18]. This transition reflects a fundamental shift from efficiency optimization to governance intelligence and transparency-oriented ESG infrastructures [19,20].

Despite this evolution, ESG information ecosystems remain structurally fragmented due to heterogeneous reporting standards, weak interoperability, and inconsistent disclosure frameworks [21]. Simultaneously, issues such as selective disclosure, data manipulation, and sustainability misrepresentation continue to undermine ESG credibility and institutional trust [22]. These conditions highlight that AI-ESG outcomes are not purely technological, but are fundamentally shaped by institutional, regulatory, and organizational governance environments [23].

Within this context, corporate reputation emerges as a critical intangible asset influencing investor confidence, stakeholder legitimacy, and long-term firm value creation. However, the relationship between AI-enabled ESG systems and reputational outcomes remains theoretically underdeveloped and empirically inconclusive. Bloomberg's Sustainability Intelligence report confirms widespread adoption of AI in ESG systems, alongside persistent concerns about transparency, auditability, and data reliability [24].

Empirical evidence further reveals substantial heterogeneity. Firms effectively deploying AI for emissions tracking, resource optimization, and standardized ESG reporting tend to achieve superior reputational outcomes [25]. In contrast, Indonesian manufacturing firms have experienced reputational deterioration due to ESG inconsistencies identified in sustainability audits, whereas firms such as Astra International and Unilever Indonesia have realized reputational gains through AI-enabled ESG systems [26]. These divergent outcomes indicate that AI-ESG-reputation effects are conditional on governance quality, data maturity, and organizational absorptive capacity [27].

Financial performance further operates as a structural boundary condition shaping AI-ESG effectiveness. Firms with stronger financial capacity are better positioned to invest in AI infrastructure and sustain ESG integration processes [28,29], whereas financially constrained firms face adoption barriers that limit ESG consistency and reputational returns [30]. However, this moderating mechanism remains insufficiently theorized, particularly in emerging market contexts.

Figure 1 conceptualizes Artificial Intelligence (AI) as a socio-technical enabler of Environmental, Social, and Governance (ESG) performance enhancement, rather than a monolithic system. It integrates key AI capabilities---machine learning, data analytics and big data, natural language processing, and automation and robotics---as complementary technological building blocks that collectively support ESG-related information processing, prediction, and decision support within organizations. However, the influence of these AI capabilities on ESG outcomes is not direct; it is mediated by organizational and institutional conditions such as data quality, absorptive capacity, and governance structures that shape how AI outputs are interpreted and operationalized. Through these mediated pathways, AI contributes to improved environmental monitoring and resource optimization, enhanced social risk detection and stakeholder analysis, and strengthened governance transparency and compliance mechanisms. Collectively, these interactions illustrate how AI-enabled systems can support more effective and responsive ESG performance, although their actual impact remains contingent on contextual and regulatory environments [31,32,33].

1.2. Research Gaps, Objectives, and Contributions

Despite the rapid diffusion of Artificial Intelligence across Environmental, Social, and Governance systems, the literature remains constrained by persistent structural, institutional, and epistemic limitations. These include fragmented ESG data infrastructures, algorithmic bias and opacity, regulatory fragmentation across jurisdictions, unresolved ethical and socio-economic risks, and the rising environmental footprint of energy-intensive AI systems. Additional gaps relate to limited model explainability and auditability, weak cross-country evidence on regulatory effectiveness, underdeveloped lifecycle assessment frameworks, and insufficient safeguards against greenwashing and machine-washing in AI-enabled ESG disclosures [34,35,36].

To address these limitations, this study conducts a systematic literature review (SLR) and conceptualizes AI-ESG integration as a socio-technical governance process through which AI reconfigures ESG analytics, disclosure architectures, organizational governance mechanisms, and sustainability decision-making processes. The objective is to integrate fragmented evidence into a coherent, theory-driven understanding of AI's systemic role in ESG transformation.

Research Questions:

RQ1. How does AI reshape ESG systems and governance?
RQ2. What are the main AI application domains in ESG?
RQ3. What barriers constrain AI adoption in ESG?
RQ4. What key theoretical and methodological gaps exist?
RQ5. What future research directions support responsible AI in ESG?

Research Objectives:

RO1. Examine AI's impact on ESG systems and governance.
RO2. Develop a taxonomy of AI applications in ESG.
RO3. Analyze barriers to AI adoption.
RO4. Identify key research gaps.
RO5. Propose future research directions.

This study contributes in four ways. First, it provides a systematic synthesis of fragmented AI-ESG literature. Second, it advances a socio-technical governance perspective by conceptualizing AI as an infrastructural force reshaping ESG analytics, disclosure systems, and organizational decision-making. Third, it develops a structured taxonomy of AI applications and barriers within ESG ecosystems. Finally, it proposes a forward-looking research agenda emphasizing responsible, transparent, and explainable AI to strengthen ESG governance and sustainability outcomes.

The remainder of the paper is organized as follows. Section 2 presents the literature review and theoretical background. Section 3 explains the systematic review methodology and gap analysis.

Section 4 develops the conceptual framework and future research agenda. Section 5 concludes the study and discusses its implications.

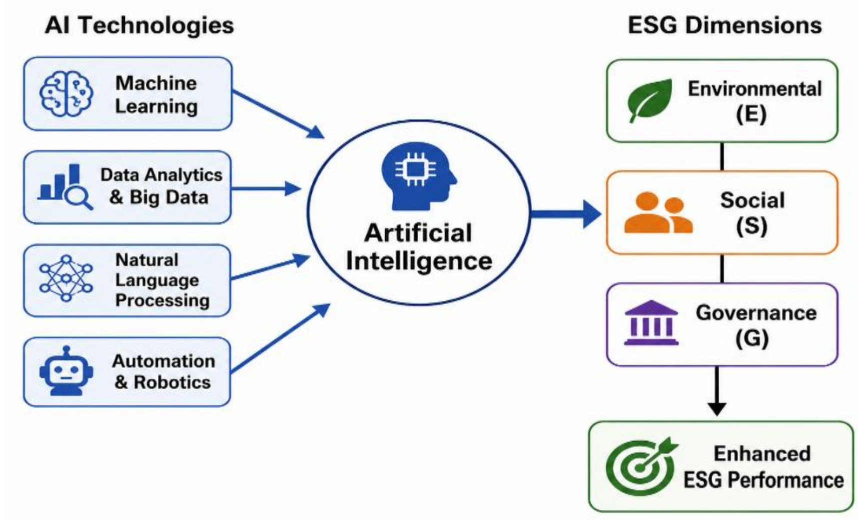

Figure 1. Artificial Intelligence in ESG Performance

2. LITERATURE REVIEW

This study adopts a PRISMA 2020-compliant systematic literature review (SLR), complemented by interpretive thematic synthesis, to ensure analytical rigor, transparency, and theory-building validity [37]. The review synthesizes 87 peer-reviewed studies (2010-2026) on artificial intelligence in ESG systems, sustainability analytics, and governance transformation. It is grounded in a socio-technical systems perspective, conceptualizing AI as an embedded governance infrastructure shaping the co-evolution of technological capabilities, institutional arrangements, and ESG decision architectures.

1) Knowledge Base Construction: The literature base was constructed through systematic searches in Scopus, Web of Science, IEEE Xplore, and ScienceDirect using theoretically informed keyword clusters related to artificial intelligence, ESG systems, sustainability analytics, digital transformation, and governance frameworks. Boolean operators were applied to ensure conceptual coverage across technological, organizational, and institutional dimensions. The search was restricted to English-language peer-reviewed journal articles published between 2010 and 2026 to ensure methodological consistency and temporal comparability.
2) Study Selection and Evidence Filtering (PRISMA-Aligned): Study selection followed PRISMA 2020 guidelines to ensure reproducibility and transparency. The initial search returned 342 records, reduced to 256 after removing 86 duplicates. Title and abstract screening excluded 173 records due to limited relevance to AI-enabled ESG integration, leaving 83 studies for full-text assessment. Full-text review excluded 19 studies based on insufficient methodological rigor, weak ESG alignment, or purely descriptive treatment of AI applications. To enhance conceptual completeness and mitigate publication bias, backward and forward citation tracking identified 23 additional eligible studies. The final evidence base consists of 87 peer-reviewed studies, forming a robust corpus for thematic synthesis. The full selection process is presented in Figure 2 (PRISMA flow diagram).
3) Quality Appraisal and Analytical Validity: A structured quality appraisal protocol was implemented to ensure methodological robustness and interpretive reliability. Each study was assessed based on research design clarity, methodological rigor, analytical validity, and

relevance to AI-enabled ESG transformation. Only studies meeting predefined quality thresholds were included, ensuring consistency across heterogeneous empirical and conceptual approaches while minimizing interpretive bias.

4) Interpretive Thematic Synthesis and Conceptual Structuring: Data synthesis followed an interpretive thematic synthesis approach, enabling iterative coding and abstraction into higher-order analytical themes. This process identifies recurring patterns across AI applications in ESG systems, governance mechanisms, sustainability analytics, and decision intelligence infrastructures. The synthesis moves beyond descriptive aggregation toward conceptual structuring, supporting taxonomy development and theory elaboration on AI-driven ESG transformation.
5) Theoretical Framing and Socio-Technical Positioning: The study is anchored in socio-technical systems theory, positioning artificial intelligence as an embedded governance mechanism rather than an autonomous technological artifact. This perspective enables a multi-level understanding of ESG transformation as a co-evolutionary process shaped by institutional constraints, organizational capabilities, and computational infrastructures, ultimately reshaping governance logics, accountability structures, and sustainability decision-making systems.

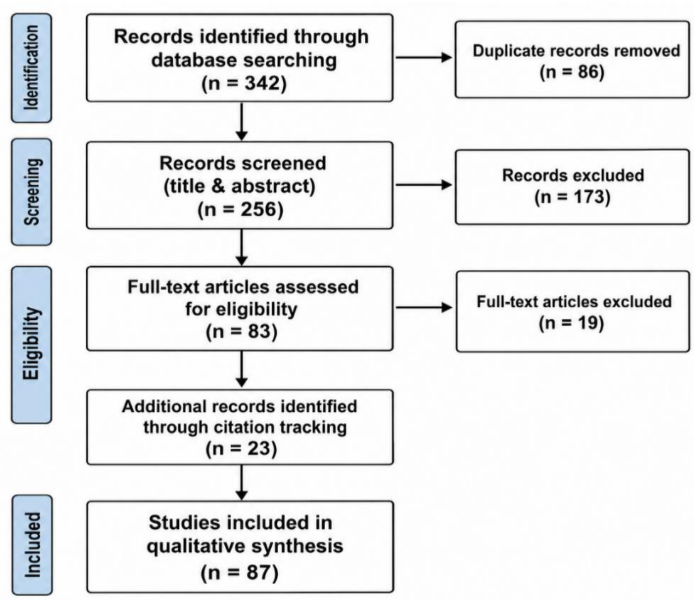

Figure 2. PRISMA flow diagram

2.1. Artificial Intelligence, ESG Foundations, and Theoretical Perspectives

Artificial intelligence (AI) is conceptualized as computational systems capable of simulating human cognitive functions such as learning, reasoning, and adaptive problem-solving. Acemoglu & Restrepo [38] define AI as "the study and development of intelligent (machine) agents that act intelligently by recognizing and responding to their environment," framing AI as an adaptive socio-technical decision infrastructure embedded within dynamic environments rather than a discrete technological artifact [39,40,41].

From a computational systems perspective, AI operates through large-scale data infrastructures that enable probabilistic inference, prediction, and optimization under uncertainty [42]. This represents a paradigmatic shift in organizational rationality from rule-based decision-making toward algorithmically mediated decision systems, extending AI from operational automation to structural reconfiguration of economic and organizational systems [43,44]. AI has evolved into a general-purpose technological infrastructure underpinning contemporary organizational intelligence system [45,46].

Despite this evolution, dominant scholarship remains anchored in an efficiency-centered paradigm, emphasizing productivity gains and labor substitution through automation of routine cognitive tasks [47]. Simultaneously, AI is framed as a complementary "virtual workforce" augmenting human capabilities [48], while robotics and autonomous systems reshape organizational hierarchies and control architectures. However, this literature remains theoretically constrained by an input-output efficiency logic and insufficiently accounts for AI as an institutional technology that actively produces legitimacy structures, accountability regimes, and evaluative infrastructures.

Within parallel scholarship, ESG frameworks emerged as a response to the increasing need for integrating non-financial risks into corporate decision-making, initially articulated through the "Who Cares Wins" initiative [49,50]. ESG thus operates not merely as a disclosure mechanism but as a strategic governance architecture enabling long-term value creation, externality internalization, and stakeholder legitimacy alignment [51,52].

However, ESG remains conceptually fragmented due to institutional divergence, regulatory heterogeneity, and competing political interpretations [53,54]. It is broadly defined as the integration of environmental, social, and governance dimensions into corporate strategy and decision-making [55], functioning as a composite institutional construct of sustainability performance [51]. The environmental dimension reflects ecological constraints and resource efficiency, the social dimension captures stakeholder legitimacy and relational equity, and the governance dimension concerns transparency, control systems, and accountability structures [56].

ESG disclosure has undergone institutional maturation from voluntary narrative reporting to standardized, audit-like regimes shaped by global governance architectures [57,58]. Empirically, ESG performance is consistently associated with improved firm valuation and financial outcomes [59], with governance quality exhibiting the strongest marginal explanatory power [60]. Mechanistically, ESG reduces information asymmetry, strengthens stakeholder trust, enhances creditworthiness, and improves financial resilience [61].

Cross-country evidence further demonstrates a robust inverse relationship between ESG performance and corporate risk across heterogeneous institutional environments, including China [51], the US [62], India, and global samples [63,64,65]. However, this empirical stream remains predominantly outcome-centric, treating ESG as an exogenous performance variable rather than as an emergent property of digitally mediated governance infrastructures.

2.2. AI-ESG Integration and Multi-Dimensional Sustainability Transformation

The convergence between Artificial Intelligence and Environmental, Social, and Governance represents a paradigmatic reconfiguration of contemporary sustainability governance, institutional accountability, and socio-technical regulation [66,67,68]. Increasingly, AI is embedded within ESG infrastructures as a data-intensive governance mechanism that enables continuous monitoring, predictive sustainability analytics, automated disclosure, and real-time optimization of socio-environmental systems. This convergence signals the emergence of an algorithmically mediated sustainability regime, in which ESG governance is progressively reconstituted through computational intelligence, platform data infrastructures, and automated decision architectures [69,70].

Despite the rapid expansion of AI-ESG research, the field remains fragmented both theoretically and methodologically. Existing studies predominantly conceptualize AI as a techno-operational efficiency enhancer, while under-theorizing its institutional role in reshaping ESG disclosure regimes, accountability structures, legitimacy production, and governance rationalities. Conversely, ESG scholarship remains largely metric- and outcome-driven, privileging disclosure scores and performance indicators while neglecting the algorithmic production, epistemic construction, and governance of ESG knowledge itself. In parallel, mainstream governance theories remain insufficiently equipped to account for the rise of algorithmic governance, wherein decision authority is increasingly redistributed across corporate actors, regulators, stakeholders, and AI systems [71,72,73].

In response, this study advances a socio-technical institutional reconceptualization of AI-ESG integration, positioning AI not as a peripheral technological enabler but as a constitutive governance infrastructure that actively reshapes sustainability information ecosystems, organizational legitimacy mechanisms, and regulatory coordination logics under conditions of accelerating digital complexity.

Within this institutional configuration, AI contributes to ESG transformation through advanced sustainability analytics and reporting systems [74], enhanced resource efficiency and waste minimization capabilities [42,75], and improved predictive capacity for environmental disruptions and systemic risks [76]. Application domains span biodiversity conservation, water governance, energy systems optimization, intelligent transportation, pollution control, and climate mitigation [77,78,79]. Accordingly, AI is increasingly institutionalized as a foundational infrastructure for sustainability transitions, circular economy systems, and environmentally intelligent production regimes [80]. However, these gains are counterbalanced by significant environmental externalities associated with computational intensity, large-scale data infrastructures, and escalating energy demands [66].

1) Environmental Dimension: From an environmental governance perspective, AI enables precision-based resource allocation, intelligent recycling systems, predictive maintenance, and advanced waste-management optimization, thereby enhancing green innovation and improving operational sustainability efficiency [81,82]. AI-driven environmental systems further strengthen climate-risk modeling, emissions monitoring, ecological forecasting, and adaptive resource management. However, these advances are structurally constrained by the "red AI-green AI" trade-off, which captures the systemic tension between escalating model complexity and environmental sustainability imperatives [83]. As computational demands intensify, issues related to carbon emissions, resource depletion, electronic waste, and digital environmental footprints are becoming central to sustainability governance debates.
2) Social Dimension: Within the social dimension, AI is reshaping organizational and societal structures through advanced workforce analytics, bias mitigation in decision-making, and enhanced human capital management systems [84,85]. Simultaneously, AI expands access to healthcare, education, and stakeholder engagement through data-driven service delivery and intelligent decision-support systems [1,86,87,88]. However, these benefits are accompanied by escalating socio-ethical risks, including algorithmic discrimination, surveillance intensification, privacy erosion, labor displacement, inequality amplification, and digital exclusion [89, 90]. These dynamics foreground critical concerns regarding distributive justice, procedural fairness, and institutional legitimacy in AI-mediated ESG systems.
3) Governance Dimension: Within governance systems, AI strengthens compliance monitoring, auditing mechanisms, fraud detection, and strategic decision-support infrastructures [91,92]. AI-enabled governance architectures enhance transparency, traceability, and institutional oversight through algorithmically augmented accountability systems [93]. Nevertheless, the emergence of "machine-washing" reveals a critical limitation: AI may be deployed symbolically to signal governance sophistication without substantive transformation of accountability structures or decision rights [94]. Across ESG dimensions, AI therefore exhibits a structural duality, simultaneously enabling sustainability optimization while producing new epistemic opacity, governance complexity, and socio-technical risk [89,95,96].

Public perceptions of AI-enabled ESG systems remain highly heterogeneous across sectors, institutional environments, and temporal contexts [97]. These perceptions are increasingly shaped by media framing effects, regulatory evolution, and institutional legitimacy-signaling dynamics [98]. Accordingly, societal trust emerges as a critical mediating variable shaping the legitimacy and adoption of AI-driven ESG governance systems.

Collectively, these frameworks indicate an accelerating convergence between AI governance and ESG-oriented regulatory regimes, embedding algorithmic systems within broader sustainability, risk, and accountability infrastructures. However, global governance remains structurally fragmented due to persistent regulatory asymmetries across jurisdictions [99], with many regimes relying on soft-law instruments, voluntary compliance, and non-binding ethical codes [100], thereby limiting enforceability and institutional harmonization.

To address these limitations, governance innovations such as Responsible AI frameworks [101], regulatory sandboxes [102], and corporate digital responsibility models have emerged. Nevertheless, persistent challenges---including algorithmic bias, opacity, privacy risks, accountability deficits, and ethical uncertainty---continue to undermine governance effectiveness and institutional trust [103,104].

Within this evolving institutional architecture, AI-ESG integration is increasingly conceptualized as a strategic governance mechanism that enhances organizational risk management and enables sustainable innovation under conditions of technological uncertainty [94]. Given the dual-use nature of AI technologies, this convergence enables an integrated governance paradigm capable of simultaneously addressing technological, environmental, social, and institutional risks within a unified analytical and regulatory framework.

3. CHALLENGES, RESEARCH GAPS, AND STRATEGIC IMPLICATIONS OF AI IN ESG

The integration of artificial intelligence (AI) into environmental, social, and governance (ESG) systems has emerged as one of the most significant developments in contemporary sustainability management. By enhancing data processing capabilities, predictive analytics, real-time monitoring, and decision support, AI has expanded organizations' capacity to assess ESG performance and respond to increasingly complex sustainability challenges [49,74,105]. Nevertheless, the literature reviewed in this study indicates that AI-driven ESG transformation is not solely a technological process but a broader socio-technical governance phenomenon shaped by interactions among technological infrastructures, organizational practices, regulatory institutions, and stakeholder expectations.

While AI offers substantial opportunities to improve sustainability outcomes, its implementation is accompanied by interconnected challenges that affect the reliability, transparency, legitimacy, and long-term sustainability of ESG systems. These challenges extend beyond technical limitations and encompass issues related to data quality, algorithmic accountability, regulatory governance, ethical responsibility, environmental sustainability, and disclosure credibility. Importantly, these challenges are mutually reinforcing. For example, fragmented ESG data undermine model accuracy, limited explainability weakens stakeholder trust, regulatory fragmentation complicates accountability, and inadequate governance mechanisms increase the risks of greenwashing and machine-washing. Consequently, understanding AI-enabled ESG transformation requires a holistic perspective that recognizes the interdependence of technological, organizational, institutional, and societal factors.

Building on this perspective, the following sections synthesize the principal challenges identified in the literature, highlight critical research gaps, and discuss their strategic implications for organizations, regulators, and policymakers. Table 1 summarizes these findings.

3.1. Data and Measurement Foundations

A fundamental challenge in AI-enabled ESG systems concerns the quality, consistency, and comparability of ESG data. Although AI technologies can process vast amounts of structured and unstructured information from sustainability reports, regulatory filings, digital platforms, and external databases, the accuracy and reliability of AI-generated insights remain highly dependent on the quality of underlying data inputs. Existing ESG disclosures continue to suffer from fragmentation, inconsistency, and a lack of standardized reporting practices across organizations and jurisdictions, limiting the comparability and robustness of AI-driven analyses [106,107].

Beyond technical concerns, ESG assessments are inherently shaped by stakeholder perceptions and value judgments. Investors, regulators, consumers, and civil society actors frequently interpret sustainability performance through different lenses, resulting in divergent evaluations of ESG outcomes [97, 98]. Despite growing attention to ESG sentiment analysis, limited research has examined how stakeholder perceptions evolve over time and interact with AI-generated assessments. This represents an important research gap because stakeholder trust and legitimacy increasingly influence ESG-related decision-making. Strategically, organizations should prioritize ESG data governance, reporting standardization, and interoperability while integrating sentiment analytics into sustainability monitoring systems to better capture stakeholder expectations and emerging reputational risks.

3.2. AI Model Integrity and Trustworthiness

The effectiveness of AI-enabled ESG systems depends fundamentally on the integrity, transparency, and trustworthiness of algorithmic models. Machine learning systems may inherit and amplify biases embedded within training datasets, leading to distorted sustainability assessments, unfair evaluations, and potentially discriminatory outcomes [87]. These risks are particularly significant in ESG contexts where decisions can influence investment allocation, corporate reputation, regulatory compliance, and stakeholder trust.

Furthermore, many advanced AI models operate as "black-box" systems, limiting explainability, interpretability, and auditability [108]. The resulting lack of transparency complicates regulatory oversight and reduces stakeholder confidence in AI-generated ESG assessments. An emerging concern is the phenomenon of "machine-washing," whereby organizations symbolically promote Responsible AI initiatives without implementing substantive governance practices capable of ensuring accountability and ethical compliance [94]. Although the concept has attracted increasing scholarly attention, empirical approaches for detecting and measuring machine-washing remain underdeveloped. Future research should therefore focus on developing explainability frameworks, auditing methodologies, and measurable indicators of AI accountability. From a strategic perspective, organizations should adopt explainable AI systems, strengthen independent auditing mechanisms, and integrate AI governance into broader ESG assurance processes.

3.3. Regulatory and Institutional Environment

The governance of AI within ESG systems is characterized by a fragmented and rapidly evolving institutional landscape [99,100]. Significant differences in legal frameworks, reporting requirements, regulatory priorities, and enforcement capacities create substantial uncertainty for organizations operating across multiple jurisdictions. These inconsistencies limit the scalability of AI-enabled ESG practices and complicate efforts to establish globally comparable sustainability standards.

The literature further highlights persistent enforcement gaps that weaken regulatory effectiveness and increase reliance on voluntary compliance mechanisms and soft-law approaches [109]. Despite growing policy attention to both AI governance and ESG regulation, limited evidence exists regarding the comparative effectiveness of alternative regulatory models across national and institutional contexts. Consequently, a major research gap concerns understanding how different governance arrangements influence organizational behavior, transparency, and sustainability outcomes. Strategically, these findings support the development of harmonized international standards, stronger enforcement mechanisms, and adaptive regulatory instruments such as regulatory sandboxes that can balance innovation with accountability.

3.4. Socioeconomic and Ethical Impacts

The increasing integration of AI into ESG systems generates important socioeconomic and ethical implications that extend beyond organizational boundaries. While AI can improve operational efficiency and sustainability performance, it may also contribute to privacy violations, algorithmic discrimination, workplace surveillance, and labor displacement resulting from automation [89,90].

These concerns raise broader questions regarding fairness, social inclusion, and the distribution of costs and benefits associated with AI-driven sustainability transformation.

At the organizational level, the capacity to adopt AI-enabled ESG practices is often shaped by financial resources and technological capabilities. Firms with stronger financial positions generally possess greater ability to invest in advanced analytics, digital infrastructure, and sustainability innovation, enabling more comprehensive AI-ESG integration [110,111]. However, existing evidence remains limited regarding the financial thresholds necessary for successful implementation and the long-term labor market consequences of AI adoption. Future research should examine how AI-driven ESG transformation affects different industries, workforce groups, and organizational contexts over time. Strategically, organizations and policymakers should pursue responsible transition strategies that combine technological innovation with workforce reskilling, social protection, and inclusive development objectives.

3.5. Environmental Sustainability of AI

AI occupies a paradoxical position within sustainability governance. On the one hand, AI contributes to environmental objectives through enhanced emissions monitoring, climate forecasting, resource optimization, and environmental risk management [49,112]. On the other hand, AI systems themselves generate significant environmental burdens through energy-intensive computation, large-scale data processing, and expanding digital infrastructure requirements [66,113].

This dual role creates a critical tension within AI-driven ESG transformation. Although AI is increasingly promoted as a sustainability-enabling technology, relatively little research has systematically assessed its full environmental footprint throughout the technology lifecycle. The absence of standardized lifecycle assessment methodologies limits the ability of organizations and policymakers to evaluate the net environmental impact of AI deployment. Consequently, future research should prioritize lifecycle-based evaluation frameworks that account for energy consumption, carbon emissions, resource utilization, and infrastructure impacts. Strategically, these findings support the development of “green AI” approaches emphasizing energy-efficient algorithms, sustainable computing infrastructure, and environmentally responsible innovation.

3.6. Governance Integration

Despite the inherently interconnected nature of ESG objectives, much of the existing literature continues to examine environmental, social, and governance dimensions separately [114]. This fragmentation limits understanding of how AI simultaneously influences multiple ESG outcomes and constrains the development of comprehensive governance frameworks capable of addressing trade-offs and synergies among sustainability objectives.

The literature also reveals a broader interdisciplinary gap. Research on AI-enabled ESG transformation remains dispersed across sustainability, information systems, finance, ethics, law, and public policy disciplines, resulting in limited theoretical integration and fragmented governance perspectives. Consequently, a significant research gap concerns the development of unified AI-ESG governance frameworks capable of integrating technological, organizational, regulatory, and societal considerations. Strategically, organizations should move toward holistic governance models that align AI governance principles with ESG objectives and facilitate coordination among internal and external stakeholders.

3.7. Market and Disclosure Outcomes

AI is increasingly reshaping ESG disclosure practices through automated reporting, predictive analytics, natural language processing, and real-time monitoring capabilities. These technologies can improve reporting efficiency, enhance information availability, and support more timely sustainability decision-making. However, they also introduce new risks related to greenwashing and machine-washing, potentially undermining the credibility and legitimacy of ESG disclosures [25,94,115].

A central concern is that AI-generated sustainability information may create an appearance of transparency without necessarily improving underlying disclosure quality. Existing assurance and verification mechanisms have not evolved at the same pace as AI-enabled reporting technologies, creating significant challenges for validating the accuracy and credibility of disclosed information. As a result, limited understanding exists regarding the effectiveness of disclosure assurance frameworks in AI-driven reporting environments. Future research should investigate mechanisms for validating AI-generated ESG information and strengthening stakeholder confidence in sustainability disclosures. Strategically, organizations should enhance transparency regarding AI usage in reporting processes, establish independent verification mechanisms, and strengthen disclosure assurance systems to mitigate risks of sustainability misrepresentation.

3.8. Synthesis and Strategic Outlook

The findings of this review suggest that AI-driven ESG transformation is shaped by three overarching tensions. The first is an information and measurement tension arising from fragmented ESG data, divergent stakeholder interpretations, limited explainability, and concerns regarding disclosure credibility. The second is a governance and institutional tension resulting from fragmented regulatory environments, weak enforcement mechanisms, and insufficiently integrated governance frameworks. The third is a sustainability and societal tension reflecting the dual role of AI as both a sustainability enabler and a source of environmental, ethical, and socioeconomic risks.

Collectively, these tensions indicate that AI-enabled ESG transformation should be understood as a socio-technical governance challenge rather than merely a technological development. Future research should move beyond isolated examinations of ESG outcomes and instead investigate the dynamic interactions among technological capabilities, organizational practices, institutional arrangements, and stakeholder expectations. Particular attention should be directed toward ESG data standardization, explainable and trustworthy AI, machine-washing detection, lifecycle environmental assessment, regulatory harmonization, disclosure assurance mechanisms, and the long-term societal consequences of AI-enabled sustainability initiatives.

From a strategic perspective, realizing the transformative potential of AI in ESG requires the development of standardized ESG data infrastructures, transparent and auditable AI systems, harmonized regulatory frameworks, integrated governance architectures, and environmentally sustainable AI ecosystems. Addressing these priorities is essential to ensure that AI serves as a credible mechanism for accountability, sustainable value creation, and long-term ESG performance rather than a source of legitimacy deficits, symbolic compliance, or sustainability misrepresentation.

Table 1. Challenges, Research Gaps, and Strategic Implications of AI in ESG

Thematic Group	Dimension	Key Challenges	Research Gaps	Strategic Implications
1) Data & Measurement Foundations	ESG data quality & standardization	Fragmented and inconsistent ESG data limit AI reliability.	Lack of global ESG data standards.	Strengthen ESG data governance and standardization.
	Stakeholder perception & sentiment	Divergent stakeholder interpretations of ESG outcomes.	Limited evidence on ESG sentiment dynamics.	Integrate sentiment analytics into ESG monitoring.

2) AI Model Integrity & Trustworthiness	Algorithmic bias & explainability	Bias and opaque models reduce fairness and transparency.	Lack of explainable and auditable ESG-AI systems.	Adopt explainable AI and independent auditing.
	Machine washing	Symbolic rather than substantive Responsible AI adoption.	Limited empirical detection of machine-washing.	Enhance ESG assurance and disclosure verification.
3) Regulatory & Institutional Environment	Regulatory fragmentation	Inconsistent global AI governance frameworks.	Limited cross-country regulatory evidence.	Harmonize international AI-ESG standards.
	Enforcement gaps	Weak enforcement and reliance on soft-law mechanisms.	Limited evaluation of adaptive regulatory tools.	Develop adaptive and enforceable regulatory systems.
4) Socioeconomic & Ethical Impacts	Social & labor risks	Privacy risks, discrimination, and job displacement.	Limited longitudinal evidence on labor impacts.	Implement responsible AI transition and workforce policies.
	Financial capacity	Financial constraints limit depth of AI-ESG adoption.	Limited evidence on financial thresholds for adoption.	Align AI adoption with firm financial capacity and ESG maturity.
5) Environmental Sustainability	Environmental cost of AI	High energy consumption and carbon emissions.	Lack of lifecycle-based environmental assessment.	Promote green AI and energy-efficient computing.
6) Governance Integration	ESG fragmentation	Uneven impacts across ESG pillars.	Lack of integrated AI-ESG frameworks.	Develop unified AI-ESG governance models.
	Interdisciplinary gap	Limited cross-disciplinary integration.	Absence of holistic governance approaches.	Foster interdisciplinary AI-ESG governance.
7) Market & Disclosure Outcomes	Trust & credibility	Greenwashing and machine-washing risks.	Limited ESG assurance and validation mechanisms.	Strengthen ESG verification and transparency systems.

4. FUTURE RESEARCH DIRECTIONS

Building on the challenges, research gaps, and strategic implications identified in Table 1, future research on AI-driven ESG transformation should move beyond fragmented investigations of individual technologies or ESG dimensions and toward a more integrated, theory-driven, and methodologically rigorous research agenda. As illustrated in Figure 3 and Table 2, the proposed agenda comprises nine interrelated research streams that collectively capture the multifaceted nature of AI-enabled sustainability governance. These streams reflect a central insight emerging from the review: AI functions simultaneously as a sustainability enabler and a source of new governance, ethical, environmental, and institutional challenges.

The literature suggests that the effectiveness of AI in ESG is shaped by complex interactions among data infrastructures, algorithmic systems, organizational capabilities, stakeholder expectations, regulatory environments, and sustainability outcomes. Although AI substantially improves analytical capacity, decision support, and reporting efficiency, its transformative potential remains constrained by fragmented data ecosystems, opaque algorithms, inconsistent governance frameworks, ethical concerns, and significant environmental externalities. Consequently, future scholarship should conceptualize AI-driven ESG transformation as a multi-level socio-technical governance phenomenon rather than a purely technological development.

Addressing the identified research gaps requires methodological pluralism and interdisciplinary inquiry. Future studies should combine machine learning, natural language processing, computational social science, causal inference, life cycle assessment, systems dynamics, and advanced econometric techniques to capture the complex and dynamic relationships among AI adoption, governance mechanisms, organizational behavior, and sustainability outcomes. Theoretically, this agenda calls for greater integration across institutional theory, legitimacy theory, socio-technical transition theory, resource-based perspectives, dynamic capabilities, and signaling theory. Such integration is necessary to explain how technological capabilities interact with institutional pressures, organizational resources, stakeholder perceptions, and sustainability objectives across multiple levels of analysis.

4.1. Data and Measurement Foundations

The effectiveness of AI-enabled ESG systems depends fundamentally on the quality, consistency, and interoperability of underlying data infrastructures. Despite rapid advances in AI-based sustainability analytics, ESG datasets remain fragmented, inconsistently reported, and weakly standardized across firms, industries, and jurisdictions. These limitations generate measurement error, reduce comparability, and constrain the reliability of AI-driven ESG assessments. Future research should prioritize the development of globally harmonized ESG data standards, interoperable reporting architectures, and AI-enabled mechanisms for real-time data validation, anomaly detection, and data integration. Methodologically, this research stream would benefit from advanced machine learning, data engineering approaches, and cross-country panel analyses. Theoretically, such efforts contribute to strengthening measurement validity and advancing data governance perspectives within AI-ESG ecosystems.

4.2. Stakeholder Perception and Sentiment Dynamics

While existing studies predominantly focus on ESG outcomes and organizational performance, considerably less attention has been devoted to understanding how stakeholders perceive and respond to AI-enabled ESG practices. Stakeholder trust, legitimacy, and acceptance increasingly influence the effectiveness of sustainability initiatives, yet the processes through which perceptions are formed, updated, and diffused remain insufficiently understood. Future research should investigate ESG sentiment dynamics using large-scale digital trace data, social media content, and other forms of unstructured information. Techniques such as natural language processing, transformer-based sentiment analysis, topic modeling, and computational social science can provide deeper insights into legitimacy formation and stakeholder responses. Theoretically, this stream extends legitimacy theory by examining how perceptions of responsible AI and sustainability evolve within increasingly digitalized information environments.

4.3. AI Model Integrity and Trustworthiness

Ensuring the integrity and trustworthiness of AI systems represents a critical prerequisite for sustainable ESG governance. Persistent concerns regarding algorithmic bias, limited explainability, weak auditability, and symbolic compliance continue to challenge the credibility of AI-enabled ESG applications. In particular, the emerging phenomenon of machine-washing raises important questions regarding whether organizations genuinely implement responsible AI practices or merely communicate such commitments symbolically. Future research should focus on developing explainable, auditable, and fairness-aware AI architectures specifically designed for ESG contexts. In parallel, scholars should develop robust methodologies for detecting algorithmic bias, assessing accountability, and identifying performative compliance behaviors. Methodologically, this stream requires explainable AI, algorithmic auditing, experimental designs, and causal inference approaches. Theoretically, it advances understanding of algorithmic accountability, trust formation, and governance within complex socio-technical systems.

4.4. Regulatory and Institutional Environment

The regulatory landscape governing AI and ESG continues to evolve rapidly, yet substantial fragmentation persists across jurisdictions. Emerging governance instruments, including the EU AI Act, NIST frameworks, and ISO standards, represent important developments, but implementation remains uneven and institutional convergence remains limited. Future research should conduct comparative analyses of regulatory regimes, evaluate the effectiveness of adaptive governance mechanisms such as regulatory sandboxes, and examine how institutional environments influence AI-ESG adoption, compliance, and innovation. Comparative institutional analysis, quasi-experimental policy evaluation, and cross-country case studies are particularly well suited to this objective. Theoretically, this stream extends institutional theory into the domain of algorithmic governance by examining processes of legitimacy formation, regulatory convergence, and institutional adaptation.

4.5. Socioeconomic and Ethical Impacts

The diffusion of AI within ESG systems generates far-reaching socioeconomic and ethical consequences that extend beyond organizational performance. Key concerns include labor displacement, inequality, privacy risks, algorithmic discrimination, and the uneven distribution of benefits associated with technological transformation. Existing research provides limited long-term evidence regarding how AI reshapes labor markets, employment structures, and social welfare outcomes. Future studies should investigate workforce reallocation, inequality dynamics, ethical risks, and societal resilience using longitudinal datasets, survey-based methods, and advanced econometric identification strategies. Theoretically, this stream contributes to socio-technical transition theory and responsible innovation research by linking technological diffusion to societal welfare, inclusion, and distributional justice.

4.6. Financial Capacity and Firm Heterogeneity

The outcomes of AI-enabled ESG initiatives vary substantially across firms due to differences in financial resources, governance quality, organizational capabilities, and absorptive capacity. Yet the conditions under which organizations successfully leverage AI for sustainability remain poorly understood. Future research should identify threshold conditions, boundary effects, and contextual moderators that shape AI-ESG adoption and performance. Large-scale panel datasets, interaction models, moderated mediation analyses, and longitudinal designs offer promising methodological approaches. Theoretically, this stream extends the resource-based view and dynamic capabilities theory by explaining heterogeneous organizational responses to sustainability pressures and digital transformation opportunities.

4.7. Environmental Sustainability of AI

AI occupies a paradoxical position within sustainability governance. While it supports emissions monitoring, environmental forecasting, resource optimization, and climate mitigation efforts, it simultaneously generates environmental costs through energy-intensive computation, large-scale data processing, and expanding digital infrastructure requirements. Existing research has not adequately quantified the full environmental footprint of AI systems across their lifecycle. Future research should employ life cycle assessment, system dynamics simulation, and optimization modeling to evaluate environmental impacts from model development through deployment and maintenance. Simultaneously, scholars should investigate the design and effectiveness of energy-efficient "green AI" architectures. Theoretically, this stream advances sustainable computing and green transition theory by explicitly examining the environmental trade-offs associated with digital sustainability technologies.

4.8. Governance Integration

Perhaps the most important challenge identified in this review is the persistent fragmentation of AI-ESG scholarship. Existing research frequently examines environmental, social, and governance dimensions independently, limiting understanding of how AI simultaneously influences multiple sustainability outcomes and governance processes. Future research should therefore prioritize the development of integrated AI-ESG governance frameworks capable of capturing interdependencies, feedback loops, trade-offs, and synergies across ESG dimensions. Systems dynamics modeling, network analysis, and structural equation modeling offer promising methodological tools for examining these complex relationships. Theoretically, this stream lays the foundation for an integrated ESG systems perspective in which AI functions as a cross-cutting governance infrastructure linking environmental performance, social responsibility, and organizational accountability.

4.9. Market and Disclosure Outcomes

AI is increasingly transforming ESG disclosure practices, sustainability reporting, and capital market behavior. Although AI enhances reporting efficiency, analytical sophistication, and information availability, it also introduces risks related to greenwashing, machine-washing, and informational manipulation. These risks may undermine disclosure credibility, investor trust, and market efficiency. Future research should investigate how AI-generated ESG information influences stakeholder decision-making, market reactions, disclosure quality, and corporate legitimacy. Textual analytics, event-study methodologies, archival financial econometrics, and causal inference approaches offer valuable methodological pathways. Theoretically, this stream extends signaling theory and disclosure credibility frameworks into algorithmically mediated information environments.

4.10. Integrative Research Agenda and Strategic Outlook

Collectively, the proposed research agenda suggests that the future of AI-driven ESG scholarship lies in understanding how technological capabilities, organizational resources, institutional arrangements, stakeholder expectations, and sustainability outcomes interact within an integrated governance ecosystem. Rather than treating data quality, algorithmic accountability, regulatory effectiveness, organizational heterogeneity, environmental sustainability, and disclosure credibility as independent concerns, future research should examine their dynamic interdependencies and cumulative effects on ESG performance.

Accordingly, AI-driven ESG transformation should be conceptualized as a multi-level socio-technical governance phenomenon that spans technological, organizational, institutional, market, and societal domains. Advancing knowledge in this field therefore requires stronger theoretical integration across institutional, legitimacy, socio-technical transition, resource-based, dynamic capabilities, and signaling perspectives. Methodological progress likewise depends on combining computational methods with rigorous causal inference, systems-based modeling, and interdisciplinary empirical approaches.

Ultimately, a mature research agenda must move beyond isolated examinations of AI applications and toward the development of holistic analytical frameworks capable of explaining the complex, dynamic, and context-dependent nature of AI-enabled sustainability governance. Such frameworks are essential for ensuring that AI contributes to transparent, accountable, and genuinely sustainable ESG transformation while mitigating the risks of legitimacy deficits, symbolic compliance, and sustainability misrepresentation.

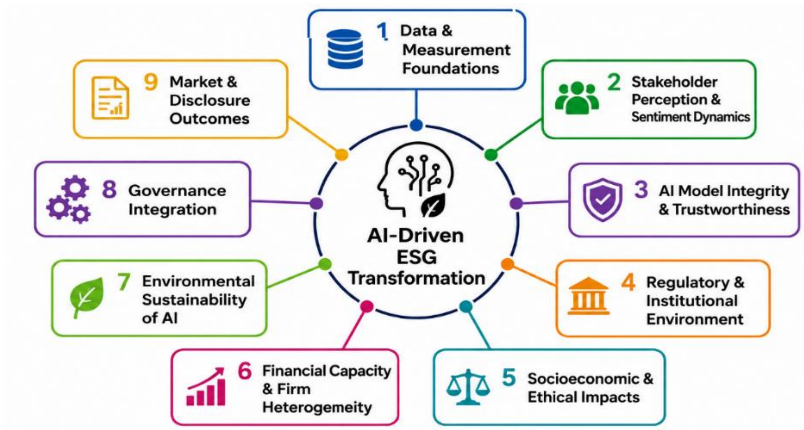

Figure 3. Structured Future Research Agenda for AI-Driven ESG Transformation

Table 2. Future Research Agenda for AI in ESG

#	Dimension	Key Research Gaps	Future Research Directions	Methods	Theoretical Advancement
1	Data & Measurement	Weak standardization, comparability, and interoperability of ESG data	Develop globally harmonized ESG data standards and AI-enabled validation and assurance systems	Machine learning, data engineering, panel analysis	Measurement validity; data governance theory
2	Stakeholder Perception	Limited understanding of ESG sentiment formation and dynamics across contexts	Examine how ESG perceptions, narratives, and sentiment evolve across stakeholders and institutional settings	NLP, transformer models, digital trace data	ESG legitimacy theory
3	AI Model Integrity	Bias, opacity, and ESG “machinewashing” risks	Develop explainable, auditable, and bias-mitigated AI systems for ESG assessment	Explainable AI (XAI), algorithmic auditing, causal inference	Algorithmic accountability theory

4	Regulation & Institutions	Fragmented, inconsistent, and evolving governance frameworks	Conduct comparative analyses of AI-ESG regulatory regimes and their effectiveness	Comparative policy analysis, qualitative comparative analysis	Institutional theory
5	Socioeconomic & Ethics	Limited longitudinal evidence on social and ethical consequences of AI in ESG	Investigate labor market effects, inequality dynamics, and ethical trade-offs of AI-enabled ESG systems	Panel data analysis, surveys, econometric modeling	Socio-technical transition theory
6	Firm Heterogeneity	Unclear thresholds and contingencies in AI-driven ESG adoption	Examine how financial resources, capabilities, and organizational readiness shape AI-ESG adoption	Panel regressions, interaction models	Resource-based view (RBV)
7	Environmental Impact	Lack of lifecycle assessment of AI systems themselves	Quantify environmental footprint of AI and develop energy-efficient "green AI" solutions	Life-cycle assessment, simulation, optimization models	Sustainable computing / green AI theory
8	Governance Integration	Fragmented treatment of ESG pillars in AI applications	Develop integrated AI-enabled ESG governance frameworks that capture cross-pillar interactions	Systems dynamics modeling, structural equation modeling	Integrated ESG systems theory
9	Market & Disclosure	Limited evidence on credibility, manipulation, and ESG trust dynamics	Examine effects of AI on ESG disclosure quality, market credibility, and signaling efficiency	Text analytics, event studies	Signaling theory

Figure 4 presents a socio-technical governance map of the AI-enabled ESG research agenda, organizing the nine research streams into three analytically distinct but interdependent layers: technological, organizational, and institutional. Rather than treating these streams as independent themes, the figure conceptualizes them as a nested and interactive system, where developments in one layer condition and reshape dynamics in the others.

At the technological layer, the figure groups streams that concern the design, performance, and externalities of AI systems themselves. This includes Data & Measurement, AI Model Integrity, and Environmental Impact. Together, these streams address foundational issues such as ESG data quality and standardization, algorithmic bias and explainability, and the environmental footprint of AI computation. This layer represents the infrastructural basis upon which ESG analytics and decision-support systems are built.

The organizational layer captures how firms internalize and operationalize AI for ESG purposes. It includes Firm Heterogeneity, Governance Integration, Stakeholder Perception, and Socioeconomic & Ethics. These streams reflect how organizational capabilities, resources, ethical considerations, and interpretive processes shape the translation of AI outputs into ESG-related actions. Importantly, this layer acts as a mediating space, where technological capabilities are filtered through managerial decisions, institutional logics, and internal governance structures.

At the institutional layer, the figure positions Regulation & Institutions and Market & Disclosure. These streams reflect the broader external environment in which AI-enabled ESG systems operate, including regulatory frameworks, compliance regimes, market-based signaling mechanisms, and legitimacy pressures. This layer establishes the rules of the game, shaping both the incentives for AI adoption and the acceptable boundaries of ESG disclosure and accountability.

Crucially, Figure 4 emphasizes cross-layer interdependencies. Technological advancements (e.g., improved explainability or better ESG data validation) directly influence organizational adoption and governance practices, while organizational experiences feed back into institutional change through regulation, market trust, and disclosure norms. Similarly, institutional pressures such as regulation and ESG reporting standards recursively shape both organizational strategies and technological design choices.

Overall, Figure 4 advances the paper's conceptual contribution by moving from a static taxonomy of research gaps to a dynamic, layered socio-technical governance framework, illustrating how AI-driven ESG research streams are structurally interconnected rather than isolated domains.

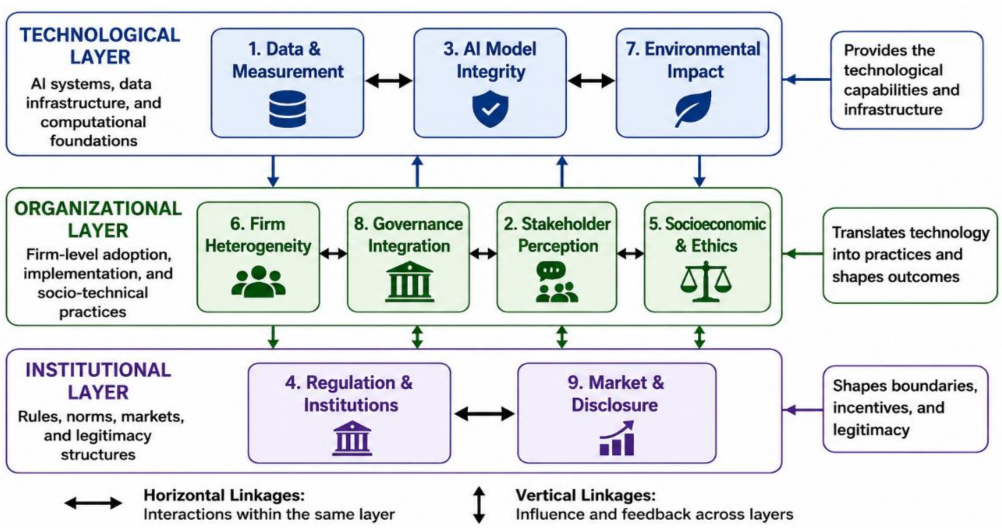

Figure 4. Multi-Layer Socio-Technical Mapping of AI-Enabled ESG Research Agenda (Technological, Organizational, and Institutional Levels)

5. CONCLUSION AND FUTURE WORK

This study systematically examined the evolving convergence between Artificial Intelligence (AI) and Environmental, Social, and Governance (ESG) systems, conceptualizing AI-enabled ESG integration as a socio-technical governance transformation embedded within organizational, institutional, and regulatory structures. The findings demonstrate that AI is increasingly reshaping ESG systems through advanced data integration, predictive sustainability analytics, automated disclosure mechanisms, and real-time decision-support capabilities. In doing so, AI is reconfiguring sustainability measurement, governance processes, organizational accountability, and ESG-related decision architectures.

Despite these advancements, the review identifies persistent structural and institutional constraints that undermine the reliability, transparency, and legitimacy of AI-enabled ESG systems. These include fragmented ESG data infrastructures, algorithmic opacity and bias, regulatory fragmentation across jurisdictions, unresolved ethical and socioeconomic concerns, and the growing environmental footprint associated with energy-intensive AI systems. Additional limitations involve weak explainability and auditability of AI models, insufficient cross-country evidence regarding regulatory effectiveness, underdeveloped lifecycle assessment frameworks, and inadequate safeguards against greenwashing and machine-washing within AI-mediated ESG disclosures.

From a theoretical perspective, this study advances the literature by reconceptualizing AI as an institutional governance infrastructure rather than a neutral technological instrument. This framing positions ESG systems as algorithmically mediated governance arrangements characterized by distributed agency, evolving institutional logics, and increasingly complex accountability structures. Accordingly, the study extends socio-technical governance theory by explaining how AI reshapes sustainability disclosure regimes, legitimacy formation processes, and the production and validation of sustainability knowledge under conditions of accelerating digitalization.

Future research should prioritize the development of standardized and interoperable ESG data infrastructures, explainable and auditable AI systems, and harmonized regulatory frameworks capable of enhancing cross-jurisdictional coherence and enforcement effectiveness. Additional research is required to examine stakeholder perception dynamics, firm-level heterogeneity, and the broader socioeconomic and ethical implications of AI deployment in ESG contexts, alongside its environmental externalities. Methodologically, advancing this field requires stronger interdisciplinary integration of machine learning, econometrics, natural language processing, causal inference, and lifecycle assessment approaches to capture both systemic governance effects and micro-level organizational dynamics.

Overall, advancing this research agenda is essential to ensure that AI strengthens ESG transparency, accountability, and sustainability performance rather than reinforcing informational asymmetries, institutional fragmentation, or symbolic compliance practices.

Theoretical Implications: This study advances socio-technical governance and ESG scholarship by conceptualizing AI as an institutional governance infrastructure that reshapes sustainability measurement, accountability systems, and legitimacy formation processes. It extends algorithmic governance theory by positioning ESG as a dynamic, data-intensive institutional field increasingly mediated through computational and algorithmic systems.

Practical Implications: The findings highlight the need for integrated AI-ESG governance frameworks that ensure transparency, traceability, explainability, and auditability of algorithmic systems. Policymakers and standard-setting bodies should prioritize regulatory harmonization, ESG data interoperability, and enforceable accountability mechanisms to enhance the credibility, comparability, and integrity of AI-enabled sustainability reporting.

Managerial Implications: Managers should treat AI-enabled ESG systems as strategic governance infrastructures rather than operational tools. This requires strengthening ESG data governance, adopting explainable and auditable AI systems, institutionalizing independent assurance mechanisms, and embedding responsible AI principles into sustainability strategies to mitigate regulatory, reputational, ethical, and operational risks.

Study Limitations: This study is limited to peer-reviewed English-language publications indexed in major academic databases, which may exclude relevant regional and practitioner-based evidence. The rapidly evolving nature of AI and ESG governance may also affect the temporal robustness of findings. In addition, the study is conceptual in nature and does not empirically validate the proposed framework. Finally, heterogeneity in ESG standards and institutional contexts across countries may constrain the generalizability of the results.

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Data Availability Statement: All data supporting this study are contained within the article.

ABBREVIATIONS

Abbreviation	Full Term	Short Definition
AI	Artificial Intelligence	Systems capable of learning, reasoning, and decision-making from data
CC	Cognitive Capabilities	AI-driven abilities for perception, learning, and decision-making
CE	Circular Economy	An economic system based on resource reuse, recycling, and regeneration
CPS	Cyber-Physical Systems	Integrated digital-physical systems for real-time monitoring and control
DM	Digital Maturity	Degree of digital integration and data readiness in organizations
DT	Digital Twin	Virtual representation of physical systems for simulation and optimization
EI	Environmental Intelligence	Integration of environmental factors into decision-making systems
HAIC	Human-AI Collaboration	Cooperative decision-making between humans and AI systems
IoT	Internet of Things	Network of connected devices enabling data exchange
KPI	Key Performance Indicator	Metric used to evaluate system performance

ML	Machine Learning	AI techniques for pattern learning and prediction
SP	Sustainable Performance	Combined economic, environmental, and social outcomes

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