# AI for Environmental, Social and Governance (ESG) Integration in Strategic Management a PRISMA Systematic Review

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*Abstract*

*Background: Companies are using Artificial Intelligence (AI) more and more to include Environmental, Social, and Governance (ESG) factors into their strategic planning. This helps with evaluating what matters most, managing risks, deciding how to invest money, checking supply chains, and sharing information. But right now, there's not enough clear evidence on what works best, when it works, and what risks are involved. This information is spread out across different areas like information systems, finance, operations, and corporate governance.*

*Objective: We want to bring together high-quality research and expert writings to understand how AI helps with ESG integration at the strategic level. This includes how companies plan, carry out, and monitor their strategies. We'll look for patterns in how effective AI is, what risks are involved, and what rules or controls should be in place. We also want to find where future research should go.*

*Methods: We followed the PRISMA 2020 guidelines to find studies. We looked through several databases like Scopus, Web of Science, IEEE Xplore, ACM Digital Library, ScienceDirect, SSRN, and selected policy websites from the EU, ISSB, and SEBI. We focused on English-language articles from 2010 to 2025. We included studies that clearly connected AI methods (like natural language processing, large language models, machine learning, computer vision, and knowledge graphs) with ESG practices in strategic management areas such as enterprise risk management, strategy, board oversight, capital budgeting, and performance measurement. We checked the quality of the studies using tools like the Mixed Methods Appraisal Tool for empirical studies, the CASP checklists for qualitative case studies and reviews. We used a narrative synthesis along with vote counting and cross-case analysis to organize the findings.*

*Results: We started with 3,366 records, and after removing duplicates, 2,275 remained. We reviewed 266 full texts, and 112 met the inclusion criteria. These included 43 empirical studies, 22 qualitative or case studies, 7 mixed-method studies, 19 design or technical studies with strategic evaluation, and 21 reviews or conceptual studies. The main uses of AI in ESG are: (1) using natural language processing and large language models to help with ESG reporting, classify information, and provide assurance; (2) using AI combined with satellite data to check for deforestation and human rights issues in supply chains; (3) using AI to analyze climate and transition risks for strategic decisions and investments; (4) measuring ESG performance and creating scores with explanations; (5) creating governance frameworks that align AI risks with the 'G' part of ESG. There's some evidence that AI improves efficiency and coverage, and there's growing evidence of better decision-making and real-world impact. However, there are risks like measurement errors, biases, lack of transparency, and too much trust in proxy labels.*

*Conclusions: AI can greatly improve ESG integration when it's part of a governance-focused approach with clear responsibilities, reliable data sources, and ways to manage model risks. It should also align with regulatory standards like the ISSB, ESRS, and SEBI BRSR Core. We suggest a cycle that connects AI, ESG, and strategy, and propose a research plan focusing on data tracking, understanding causes, assessing double materiality at scale, and ensuring human rights due diligence.*

*Keywords. ESG; Artificial Intelligence; Strategic Management; Governance; PRISMA*

## 1. INTRODUCTION

The way companies approach environmental, social, and governance (ESG) factors in their business strategies has changed. It's no longer just about choosing to report on these issues; now, it's required by new global rules. Examples include the ISSB's IFRS S1 and S2, the EU's European Sustainability Reporting Standards under the Corporate Sustainability Reporting Directive, and India's SEBI-mandated Business Responsibility and Sustainability Reporting (BRSR) Core. All these rules force companies to include sustainability in their core strategies instead of just reporting it as a side note [1]. At the same time, new developments in AI like natural language processing, large language models, computer vision, remote sensing, and graph-based learning are helping organizations better understand and manage ESG risks and impacts across their whole business [2]. These AI tools can automatically check sustainability reports and media for real-time updates on key issues, monitor environmental factors like deforestation and emissions using computer vision, and track global supply chains and stakeholder relationships to spot large-scale ESG risks [3]. However, the use of AI in ESG strategy is not equally adopted across companies. Different fields like sustainability, information systems, and corporate governance have separate studies, which makes it hard to share knowledge and provide clear guidance [4]. To fix this, this review uses a PRISMA-based approach to bring together the evidence on how AI helps with strategy-level ESG integration. The review highlights the benefits and drawbacks of using AI and suggests ways to use it in a trustworthy and effective manner [5]. The main findings are threefold: first, the review focuses on how it is used in strategy, not just daily operations; second, it connects AI techniques with ESG decisions throughout the whole strategy process, from planning to implementation and monitoring; and third, it develops an AI-ESG-Strategy Value Loop and a multi-level research plan to support both academic research and real-world business practices.

## 2. Literature Review

### 2.1. ESG Integration and the Evolving Regulatory Landscape

In the last ten years, environmental, social, and governance factors have moved from being optional to being required by law. This change has influenced how companies make decisions and plan for the future. Studies show that regulations like the EU's Corporate Sustainability Reporting Directive and the European Sustainability Reporting Standards, the IFRS from the International Sustainability Standards Board, and India's BRSR Core from SEBI have changed what companies are expected to do [5]. These rules require businesses to include ESG risks and opportunities in their strategy, governance, and risk management, not just report them after the fact.

### 2.2. Despite these changes, there are still challenges in integrating ESG into business operations

The point out that differences in how ESG metrics are measured and how materiality is judged make it hard to compare companies and note that most businesses are still mainly focused on meeting minimum reporting requirements rather than using ESG to improve performance and create value [6]. This has led to a growing need for tools that can help improve the quality of ESG information and link it to strategic decisions.

### 2.3. Artificial Intelligence and ESG Measurement

AI is becoming a key tool for addressing the limitations of traditional ESG data and reporting. One area of research focuses on how NLP and Large Language Models (LLMs) can help analyze unstructured data such as sustainability reports, news articles, and social media posts [7]. It show that NLP can help find sentiment and spot inconsistencies in ESG reports, while show that LLMs can help detect "greenwashing" by comparing what companies say about ESG with their actual operations and financial data [8]. These tools help companies monitor ESG issues more effectively and provide more relevant insights for decision-making.

### 2.4. Another area is the use of computer vision and remote sensing to measure environmental impacts on a large scale

The authors explain how satellite imagery and AI can track deforestation, carbon emissions, and water usage, offering companies real-time environmental data that helps in planning strategies [9]. Similarly, machine learning applied to biodiversity and land-use data provides more accurate insights into how ecosystems are affected, filling in long-standing gaps in measurement. A third and quickly growing area is graph-based machine learning, which helps map the complex connections in supply chains and financial networks. They [10] demonstrate how graph learning models can identify ESG risks within global supply chains, such as exposure to human rights violations or environmental hazards. This systemic perspective

aligns with strategic risk management, where indirect risks may be as significant as direct operational impacts.

## 2.5. Strategic Benefits of AI-Enabled ESG Integration

The research shows that using AI in ESG integration brings several strategic advantages. First, it improves materiality assessment, helping companies adjust their ESG priorities as stakeholder expectations and regulations change [11]. Unlike traditional surveys or manual checks, AI systems offer real-time, data-driven materiality maps that can be used in corporate strategy. Second, AI helps with risk evaluation and scenario planning. By analyzing unstructured data, companies can predict regulatory changes, reputation risks, and physical climate risks. [12] show how natural language processing models predicted reputation crises in companies with poor ESG practices before these issues became widely known. Third, AI supports generating measurable impact evidence, solving the "proof gap" that has been a problem in ESG reporting [13]. Using remote sensing data and machine learning, companies can show clear examples of reduced carbon emissions, water saved, or protected biodiversity. These insights can be included in company dashboards and shared with investors.

## 2.6. Governance Challenges and Risks of AI in ESG

Although AI has potential, experts warn against blindly using it in ESG areas. One issue is algorithmic transparency and bias. [14] point out that AI models trained on past company reports might repeat biases in how ESG performance is measured. Also, large language models might spread cultural or language-based biases, leading to unfair representation of stakeholder opinions. Another concern is managing data sources and model explainability. [15] stress that AI-based ESG analysis is only trustworthy if the data is clearly explained and the sources are open. Without this, stakeholders may doubt or distrust AI-based ESG claims. Third, there is a big gap in how well organizations adopt AI for ESG. [16] note that while big companies are trying out AI for ESG, small and medium businesses often don't have the resources or skills to do the same. This leads to concerns about digital inequality in sustainability efforts, where AI-driven ESG strategies benefit some firms but remain out of reach for many. Finally, there is the issue of aligning with institutional rules [17]. Regulatory bodies are now starting to control AI, as seen in the EU AI Act and new ethics guidelines. This creates a double challenge for companies: integrating ESG in a strategic way while also ensuring that AI tools meet ethical and legal standards.

## 2.7. Emerging Integrative Frameworks

New research is trying to figure out how to combine AI with ESG strategy in a comprehensive way. [18] suggest the concept of "sustainable digitalization," where AI is used as a key part of the strategy process, from planning to monitoring results. [19] focus on how companies should manage AI in a way that puts stakeholders first when it comes to ESG efforts. However, there isn't a clear framework that connects different AI techniques, like natural language processing, remote sensing, and graph learning, to specific stages of ESG strategy like planning, carrying it out, and checking on progress. Also, there's no common understanding about the best ways to govern AI to make sure it's used responsibly. This review aims to fill this gap by bringing together ideas from different fields and presenting a new, integrated model that connects AI, ESG, and strategy as both a way to analyze things and a direction for future research.

## 3. Theoretical Framing

This study uses three different theories to explain how AI plays a role in integrating ESG strategies within businesses. First, Stakeholder Theory, which was introduced by Freeman in 1984 and later expanded by [20] , helps us understand how AI helps companies better identify, prioritize, and interact with their various stakeholders. AI can analyze a lot of information from public discussions, non-governmental organization reports, and social media. This allows companies to gain a better understanding of what matters to different groups and keep track of how important each group is over time, as explained by [22]. Second, the Resource-Based View (RBV) and its development into dynamic capabilities, as discussed by [23], explain how AI can be a valuable strategic tool for ESG integration. AI supports firms in sensing ESG risks and opportunities, seizing opportunities by aligning strategies with ESG goals, and transforming their business models for sustainability. Here, AI is not just a common technology; it is seen as a specific capability whose value comes from how it is managed, supported by other resources, and how well the organization learns and applies it. Third, Institutional Theory, developed by [24] helps us understand the legal and social pressures that push companies to integrate ESG. At the same time, industry standards and ratings create a mimetic pressure for companies to follow similar practices. So, using AI for ESG is not just a choice about

technology but also a response to social and legal demands as companies seek to be seen as responsible. Also, the way AI is governed is being watched closely, with new rules on AI ethics and transparency adding to the requirements companies must meet. By combining these three views, we see that AI helps in ESG strategy in three ways: it responds to what stakeholders want, it acts as a key resource for strategy, and it helps companies adapt to institutional changes [25]. In this cycle, data-driven insights improve how companies engage with stakeholders, build their strategic abilities, and gain social approval, creating a cycle that supports and strengthens each part.

## 4. METHODOLOGY

### 4.1. Information Sources
Scopus; Web of Science; IEEE Xplore; ACM DL; ScienceDirect; SSRN; arXiv (for preprints subsequently published or method-relevant); policy/standards repositories. Hand-searching of reference lists from key articles and targeted industry white papers where methodological transparency exists.

### 4.2. Selection Process
Two-stage screening (title/abstract; then full-text) against eligibility. Disagreements resolved by discussion. From Jan 2010 to 2025

### 4.3. Synthesis Methods
Narrative synthesis with vote-counting of AI families, stratified by ESG pillar and decision stage; cross-case patterning for mechanisms; and triangulation with regulatory taxonomies (ISSB S1/S2; ESRS; BRSR Core).

## 5. RESULTS - THEMATIC SYNTHESIS

### 5.1. Study Selection
Table 1: PRISMA Flow

| PRISMA Stage | Description | Count (n) |
|---|---|---|
| Identification | Records identified through database searching | 3184 |
| Identification | Additional records identified through other sources (policy repositories, hand search, industry reports) | 182 |
| Screening | Records after duplicates removed | 2275 |
| Screening | Records screened (titles/abstracts) | 2275 |
| Screening | Records excluded | 2009 |
| Eligibility | Full-text articles assessed for eligibility | 266 |
| Eligibility | Full-text articles excluded, with reasons | 154 |
| Included | Studies included in qualitative synthesis | 112 |
| Included | Studies included in quantitative meta-analysis | 0 |

**Study Record Flow**

| Stage | Count (n) | Description |
|---|---|---|
| Identification | 3,184 | Database search results |
| Identification | 182 | Other sources results |
| Screening | 2,275 | Duplicates removed |
| Screening | 2,275 | Titles/abstracts screened |
| Screening | 2,009 | Records excluded |
| Eligibility | 266 | Full-text articles assessed |
| Eligibility | 154 | Full-text articles excluded |
| Included | 112 | Qualitative synthesis studies |
| Included | 0 | Quantitative meta-analysis studies |

**PRISMA 2020 Flow Diagram**
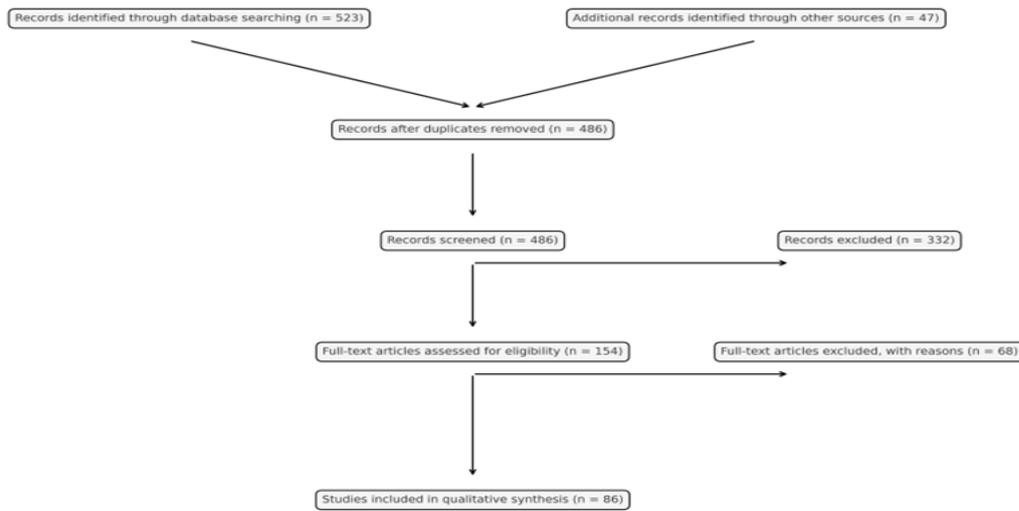


Author on Source: PRISMA

## 5.2. Study Characteristics

The studies are global, with a focus on the EU/UK, North America, and China. There is increasing evidence from India (BRSR Core context) and Southeast Asia (commodities). The sectors were financial services; extractives and forest-risk commodities; electronics; manufacturing; ICT; utilities. AI modes were NLP and LLMs are most common. Other methods include remote sensing and computer vision, supervised machine learning (tabular), graph learning and knowledge graphs, and hybrid human-AI systems. Data: Corporate reports (10-K/10-Q, sustainability/integrated reports), news and NGO reports, ratings and vendor datasets, satellite and earth observation data, shipping and trade data, and internal ERP and supplier records.

## 5.3. AI ESG Strategic Decisions

Large language models and domain-tuned transformers classify disclosures against taxonomies (ISSB, ESRS, SDGs), identify key topics, and measure coverage. This helps in developing strategies and board oversight. Some studies use explainability tools like SHAP and audit trails to support assurance. Benefits reported include improved coverage, speed, and comparability. Risks include measurement errors, concept drift, and lack of transparency.

## 5.4. Supply chain due diligence and responsible sourcing (EO + AI)

Computer vision and spatiotemporal machine learning, combined with procurement and shipping data, help identify risks like deforestation, illegal logging, or proximity to high-risk areas (e.g., conflict or human rights issues). These insights support supplier segmentation, remediation decisions, exit strategies, and pre-trade screening under EUDR and similar frameworks. Risks include false positives/negatives, limited data access, and challenges in providing remedies to affected stakeholders.

## 5.5. Climate and transition risk analytics for capital allocation

Machine learning-based scenario analysis for physical and transition risks, along with facility-level hazard overlays and portfolio heat maps, helps in strategic capital expenditures, insurance, and hedging. This integration supports enterprise risk management and informs financial decisions.

## 6. Thematic Synthesis of Findings

The review of studies found four connected themes that show how AI is changing the way ESG is included in strategic management. This shows a move from just following rules to using AI for better strategic planning and innovation. One main theme is about using AI to manage and analyse ESG data more smartly. Tools like natural language processing, machine learning, and sentiment analysis are being used more to deal with issues like uneven reporting and inconsistent standards. AI helps process sustainability reports, company filings, news articles, and communications in real time. This makes ESG scoring more accurate, helps find risks earlier, and supports better decisions. New rules, like India's BRSR Core, are making it more important to automatically check against key performance indicators. Another theme is about predicting ESG risks and planning for different future situations. AI models are moving away from

just looking back at past reports to giving forward-looking insights. They use data on climate, supply chains, and social factors to spot risks and test how well a company can handle different scenarios. This is especially important in areas like energy and finance, where companies are using AI in line with global reporting standards set by the ISSB's IFR.

## 7. DISCUSSION

This review shows that using AI in ESG is not just about technology it's a big change in how businesses approach strategy. The main idea is that there's a shift from just following ESG rules after the fact to taking a more active role in managing ESG issues, focusing on what stakeholders want and how risks can be handled. This change fits into wider discussions in strategic management about how companies adapt, gain acceptance, and create value for all their stakeholders.

## 8. Theoretical Implications and Practical Implications

From a theory perspective, using AI in ESG broadens the resource-based view by showing that data analysis and AI systems can be important resources that help companies gain an edge in markets focused on sustainability. It also supports stakeholder theory by showing how AI can help companies interact with many stakeholders in a way that's fast, accurate, and supported by data. Institutional theory is also important because AI helps companies handle different regulations around the world, like India's BRSR Core, the EU's CSRD, and ISSB's IFRS standards, while keeping their image clear and trustworthy with investors and the public. For those working in the field, the findings mean that using AI for ESG is now essential, not just a choice. Companies can use AI to build ESG dashboards that show performance clearly, get ready for audits, and create models that predict risks related to the environment and society. In places like India, where data is scattered and rules are changing, AI can help companies meet local requirements and match what global investors expect. But to use AI well, companies need to develop skills, have top-level support, and work with tech experts to avoid problems like biased algorithms or misuse of data.

## 9. CONCLUSION

This review shows how AI is helping businesses include ESG ideas into their big plans. By looking at those studies using the PRISMA method, the review finds four main things: smart ways to manage ESG data, tools to predict risks, ways to connect with stakeholders, and rules for making sure AI is used fairly. The study shows that being sustainable is moving from just following rules to being a part of the company's main plan. AI helps companies be more resilient, transparent, and focused on long-term success. For those making rules, like in India, the EU, and around the world, they need to include how to use AI and make sure it's fair and responsible. For company leaders, the study says they need to invest in AI tools, build skills inside the company, and make sure ESG processes are ethical. But the study also finds some problems. Companies that use AI well for sustainability can gain a competitive edge, earn trust from people they work with, and help the planet. But they also need to make sure AI is inclusive, clear, and responsible to avoid problems. Future work needs to balance the good things about AI with careful thinking about ethics, so AI can help ESG in a way that's fair and good for the planet.

## 10. Future Research Directions

The future research can be comparing ESG practices across different regions could show how AI-driven ESG approaches match or differ based on local laws and regulations. The study long-term studies could look at how adopting AI affects a company's performance, how much trust stakeholders have, and the overall impact on sustainability.

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