Karolina ŁUDZIŃSKA

THE FIRM-LEVEL AI-ESG PERFORMANCE NEXUS: A RAPID LITERATURE REVIEW AND FUTURE RESEARCH AGENDA

Karolina ŁUDZIŃSKA (ORCID: 0000-0002-0322-489X) – Faculty of Management, University of Warsaw

Correspondence address:
Szturmowa Street 1/3, 02-678 Warsaw, Poland
e-mail: k.ludzinska@uw.edu.pl

ABSTRACT: This exploratory study examines the relationship between artificial intelligence (AI) and corporate ESG performance. It considers both the positive impacts and potential limitations of AI deployment for ESG outcomes at the firm level, identifying key moderating variables through the lens of the Dynamic Capabilities Framework (DCF). A rapid literature review (RLR) was conducted, supplemented by a snowball search focused on Q1 and Q2 journal publications. The findings indicate a predominantly positive relationship between AI and firm-level ESG performance. The mechanisms through which AI contributes to ESG outcomes cluster around three interrelated domains: firm-level capabilities and characteristics; technological and operational mediators; and regional and contextual factors. Key contributions of AI include improvements in data processing and information governance, innovation, mitigation of greenwashing, facilitation of digital transformation, enhanced ESG operational efficiency, and stronger internal control mechanisms. However, the effectiveness of AI in improving ESG outcomes remains highly context dependent. This study contributes to the growing discourse on AI-enabled ESG transformation by offering a structured synthesis of existing research and outlining a future research agenda.

KEYWORDS: artificial intelligence, AI, ESG, ESG performance, RLR

Introduction

Today, artificial intelligence plays a significant role in realizing sustainable economic development (Chen et al., 2024). The advancement and implementation of artificial intelligence technology have become key drivers of innovation across multiple economic and societal domains (Chen & Zhang, 2024). Artificial intelligence is commonly understood as an automated technology capable of replicating human cognitive functions to perform a wide range of tasks (Russell & Norvig, 1995). In organizational theory and practice, AI is typically defined as the broad class of technology developed with the objective of collecting data in order to solve problems or make decisions (Campbell et al., 2020; Li, Zhang, & Gao, 2024). Artificial intelligence can enhance production efficiency and quality of life by augmenting human labor, while also facilitating shifts in employment types, advancing industrial development, and promoting the transition to a more sustainable energy structure (Zhang, 2024).

At the same time, new technologies have the potential to disrupt consumer behavior, management processes, and organizational strategy (Evans, 2017), and artificial intelligence is undoubtedly one such disruptive technology, affecting every aspect of organizational management. The volume of data produced by both humans and machines today exceeds the capacity of individuals to process, analyze, and make informed decisions based on it (Hurwitz et al., 2012). Artificial intelligence offers a solution to this challenge; however, it is more than just an evolution in statistics – AI facilitates data-driven learning while eliminating the need for assumptions inherent in traditional statistical methods (Campbell et al., 2020). Moreover, AI commercial applications have demonstrated characteristics of a "general-purpose technology" (Chen & Zhang, 2024).

Therefore, the demand for AI deployment within organizations is steadily increasing. According to Ayming's 2025 study, companies in Poland increasingly recognize artificial intelligence (AI) and machine learning (ML) as critical tools for process optimization and the enhancement of ESG strategies, a perspective endorsed by 37% of surveyed firms (Ayming, 2025).

Although Environmental, Social, and Governance (ESG) frameworks are gaining increasing attention, their impact on organizational performance continues to be contested (Gillan et al., 2021; Liang & Renneboog, 2021). In parallel, doubts about the authenticity of ESG initiatives have intensified, with critics arguing that many corporate actions in this area are largely symbolic and lack substantive outcomes (Winston, 2024). At the same time, there is mounting pressure from stakeholders for greater transparency in disclosing the environmental and social consequences of corporate operations (de Freitas et al., 2020). In response, regulatory bodies and lawmakers have introduced a growing number of ESG-related policies and regulations[1]. As Kuntz (2023) observes, these developments are gradually transforming corporate governance, with the expansion of ESG-related legal obligations weakening the traditional reliance on the business judgment rule. As a result, the discourse has shifted from questioning the relevance of sustainable practices to critically examining their implementation and effectiveness.

This evolving landscape of heightened expectations, regulatory scrutiny, and critical evaluation of ESG practices calls for a deeper understanding of the tools and technologies that can support meaningful implementation. In this context, artificial intelligence has emerged as a transformative force in organizational decision-making and operational efficiency. While recent research has primarily examined AI's influence on macroeconomic indicators such as economic growth, income distribution, and labor market disruption (Kar et al., 2022), the specific role of AI in shaping corporate ESG performance remains underexplored.

The motivation for examining the relationship between AI-driven ESG practices and corporate ESG performance stems from the transformative potential of artificial intelligence and its capacity to enhance the efficiency and effectiveness of organizational processes. Artificial intelligence is driving efficiencies at an unprecedented level, enabling automation and integration of business processes, which significantly impact various business functions, including marketing (Campbell et al., 2020).

1 In Europe, initiatives like the EU Taxonomy (European Commission, 2020) and the CSRD directive (European Parliament and Council, 2022) aim to enforce mandatory non-financial reporting. In the United States, the Federal Trade Commission underscores the need for clear and precise language when making environmental claims (Federal Trade Commission, 2012).

DOI: 10.34659/eis.2025.95.4.1170

This exploratory review critically examines recent literature to synthesize the key drivers behind the deployment of artificial intelligence and enhancing corporate ESG performance. By engaging with the complex intersection of AI and ESG, the study investigates both the rationale and the mechanisms through which AI is implemented at the firm level to support improved sustainability outcomes. Particular attention is given to identifying the mediating factors that influence the relationship between AI adoption and ESG performance at the firm level, with the aim of understanding the conditions under which AI can most effectively contribute to corporate sustainability efforts. The overarching objective is to illuminate this evolving area of inquiry, propose a preliminary research agenda, and lay the groundwork for more comprehensive future studies. This review is guided by the following research questions:

RQ1: How is artificial intelligence (AI) linked to corporate ESG performance in the existing literature?
RQ2: How does AI deployment at the firm level influence ESG performance?
RQ3: What factors shape the relationship between AI implementation and corporate ESG outcomes?

To address the research questions, the study adopts a Rapid Literature Review (RLR) methodology, as recommended by Barends et al. (2020) and Grant and Booth (2009), supplemented by the snowball technique (Wohlin, 2014), to systematically and efficiently identify and synthesize the existing body of research on the relationship between AI adoption and corporate ESG performance. The methodological approach is complemented by a theoretical foundation drawing on the Dynamic Capabilities Framework (Teece et al., 1997) to guide the analysis and interpretation of findings.

This paper contributes to the emerging literature at the intersection of artificial intelligence and corporate ESG performance in several ways. First, it offers a structured review and synthesis of recent studies that examine how AI implementation affects ESG outcomes at the firm level – an area that remains underexplored compared to macroeconomic analyses (e.g., Kar et al., 2022). Second, the paper identifies and evaluates the key mediating factors linking AI adoption and ESG performance, considering both enabling and constraining mechanisms. Drawing from textual analysis, a Rapid Literature Review and snowball search, the study highlights the organizational, technological, and contextual dimensions shaping this relationship. Third, it advances the discourse by outlining a future research agenda aimed at deepening the theoretical and empirical understanding of ESG performance in the context of AI adoption. Finally, by investigating the mechanisms through which AI can support or challenge ESG objectives, this study provides practical insights for firms seeking to enhance sustainability performance through technological innovation. It further broadens the understanding of how firm-level capabilities, digital maturity, and external institutional pressures interact in shaping ESG outcomes.

The paper is structured as follows: Section 2 provides the conceptual background on ESG and AI, identifying key debates and research gaps. Section 3 outlines the methodological approach, including the Rapid Literature Review and snowball sampling strategy. Section 4 presents the review of findings, categorizing both the positive and neutral/negative mediators of the AI–ESG relationship. Section 5 offers a critical discussion of these findings. Finally, Section 6 concludes by summarizing the main insights, acknowledging the study's limitations, and proposing directions for future research.

Conceptual background and identification of the research gap

The concept of Environmental, Social, and Governance (ESG) criteria emerged relatively recently, first introduced in the 2004 United Nations report *Who Cares Wins: Connecting Financial Markets to a Changing World* (UN Global Compact, 2004). Initiated by then UN Secretary-General Kofi Annan and developed by twenty financial institutions, the report sought to create a standardized set of principles for evaluating corporate performance that extended beyond conventional financial indicators.

ESG criteria were originally intended to offer investors, analysts, and other stakeholders a holistic framework for assessing companies by incorporating environmental, social, and governance dimensions into decision-making processes. However, despite widespread use, ESG still lacks a universally agreed-upon definition (Clément et al., 2022). Its multifaceted and wide-ranging nature renders the development of a comprehensive and universally applicable set of standards both difficult and arguably unattainable (Matos, 2020).

While ESG was initially tailored for the financial sector, its adoption has expanded significantly across organizational contexts due to its broader strategic value. Organizations increasingly use ESG principles to bolster their reputations (Karwowski & Raulinajtys-Grzybek, 2021; Murè et al., 2021), reduce regulatory burdens (Christensen et al., 2021; Porter et al., 2019), mitigate financial exposure (Chollet & Sandwidi, 2018), attract investment (Cheng et al., 2014), and manage reputational risks linked to environmental and social controversies (Escrig-Olmedo et al., 2019). These broader applications underscore ESG's growing relevance beyond its original investment-centred rationale.

Corporate ESG performance refers to a company's achievements across the environmental, social, and governance dimensions. In academic discourse, it is typically conceptualized as a multidimensional construct that reflects how effectively a firm manages its environmental footprint, fulfils its social responsibilities, and upholds robust governance standards. For instance, Zhang and Shi (2024) define ESG performance as a company's effectiveness in environmental protection, social contribution, and efficient governance. In essence, ESG performance captures the non-financial aspects of corporate activity related to sustainability, often referred to as the three pillars of responsible business conduct (Su, Yu, & Zhao, 2025). As Gillan et al. (2021) observe, ESG performance has become a central concern for both investors and scholars, highlighting its significance as a key component of corporate sustainability.

In both academic literature and business practice, ESG performance is assessed using composite indices and ratings based on a set of non-financial criteria. These criteria capture the degree to which a company or organization demonstrates social and environmental responsibility, ethical conduct, and sound corporate governance. ESG ratings are typically produced by private agencies and commercial firms, each employing distinct datasets, weighting schemes, and interpretations of ESG dimensions (Escrig-Olmedo et al., 2019; Kotsantonis & Serafeim, 2019, among others). Consequently, the ESG performance rating of a single organization can vary considerably across different rating providers (e.g., Berg et al., 2022).

A similar challenge arises when examining AI adoption at the firm level – efforts to quantify the extent and maturity of AI implementation remain highly fragmented. Researchers have relied on diverse proxies, such as the number of industrial robots (Chen et al., 2024), industrial intelligence indices (Lin & Xu, 2024), and the volume of AI-related patents granted (Chu et al., 2024). However, the lack of a unified and standardized framework for assessing AI development poses a significant barrier to accurately evaluating its implementation and impact across firms, industries, and regions. This gap highlights the need for greater methodological coherence and interdisciplinary research.

At the same time, AI technology is increasingly recognized as a key enabler for improving organizational efficiency, enhancing decision-making processes, and reducing operational costs (Iansiti & Lakhani, 2020). It also plays a critical role in accelerating digital transformation across industries (Holmström, 2022). AI has thus emerged as a strategic consideration for corporate leadership with firms not only applying but also actively shaping the trajectory of AI research and implementation (Davenport & Ronanki, 2018).

This transition signifies AI's evolution from a technical solution to a vital component of corporate strategy and management (Ahmed et al., 2023). Leveraging its powerful learning capabilities, along with exceptional data processing and analytical functions, AI has become increasingly integrated into business operations (Babina et al., 2024). Empirical research has confirmed AI's substantial influence at the firm level, shaping productivity, decision-making, and innovation processes (Acemoglu & Restrepo, 2018; Babina et al., 2024).

Moreover, AI technology enhances research and development efficiency by accelerating knowledge creation and facilitating technology spillovers (Cockburn et al., 2018), while also strengthening organizational learning capabilities and promoting greater investment in research and talent (Liu et al., 2020).

The impact of artificial intelligence on corporate operations is complex and multifaceted. By enhancing decision-making, improving operational efficiency, and promoting more sustainable use of resources, AI has become a pivotal tool in advancing firm-level environmental, social, and governance objectives (Burnaev et al., 2023; Mori, 2023).

Therefore, recent research increasingly recognizes the vital role of artificial intelligence in promoting environmental sustainability, with diverse algorithms supporting industries in their pursuit of genuine sustainable practices (Kar et al., 2022). AI technologies hold substantial potential to

DOI: 10.34659/eis.2025.95.4.1170

advance sustainable development through precise data analysis, intelligent optimization, and adaptive decision-support systems (Luqman et al., 2024). Furthermore, AI contributes to the global energy transition by facilitating a shift from high emission to cleaner energy sources, thereby reducing greenhouse gas emissions and supporting international climate goals (Wang et al., 2024). Finally, AI can enhance ESG reporting by enabling more transparent and decision-useful disclosures, capturing the value of data, and strengthening data governance (Leitner-Hanetseder & Lehner, 2022).

Notably, rapid advancements in AI technologies and their widespread commercial adoption have marked a significant technological shift. While these developments hold considerable potential to boost productivity growth, they may also produce mixed effects on labor markets, particularly in the short term (Furman & Seamans, 2019). Du and Xie (2021) highlight several critical ethical concerns in the development and deployment of artificial intelligence, including AI biases, ethical design, consumer privacy, cybersecurity, individual autonomy and wellbeing, and unemployment. They emphasize the need for companies to actively engage in corporate social responsibility (CSR) to guide the future of ethical AI. Furthermore, they underscore the risks associated with the potential for powerful AI systems to displace workers, an issue that should also be integrated into discussions of ESG frameworks.

Despite the growing alignment between sustainability priorities and advancements in artificial intelligence, the relationship between AI and ESG – understood as a comprehensive construct – remains under-researched. In particular, the intersection between organizational AI deployment and firm-level ESG performance has received limited scholarly attention. While the existing literature has addressed the macroeconomic implications of AI adoption and its broader sustainability effects (e.g., Kar et al., 2022), as well as its role in enhancing operational performance through digital transformation (Holmström, 2022; Iansiti & Lakhani, 2020), relatively little is known about how AI implementation affects ESG outcomes at the firm level. This gap is particularly relevant given that firms are the primary agents of both technological innovation and ESG-driven transformation. Understanding the firm-level dynamics between AI and ESG outcomes is essential for assessing how digital innovation can support, or potentially hinder, responsible and sustainable business practices. Addressing this gap can provide practical insights for corporate decision-makers, policymakers, and scholars interested in the strategic integration of AI into ESG agendas.

To address the above research gap in the existing literature, this study adopts the Dynamic Capabilities Framework (DCF) – an approach particularly well-suited to the context of emerging technologies and the evolving organizational environment they engender. The DCF posits that in rapidly changing and technologically dynamic settings, firms must continuously adapt, integrate, and reconfigure both internal and external competencies to sustain and enhance their competitive advantage (Teece et al., 1997). Crucially, the framework highlights that long-term success is not solely dependent on the possession of valuable assets, but rather on a firm's ability to innovate, learn, and effectively respond to environmental shifts. It centers on three core capabilities: the ability to sense and shape opportunities and threats; the capacity to seize those opportunities; and the competence to maintain competitiveness through the transformation of organizational resources and structures.

Moreover, the framework emphasizes that competitive advantage arises not merely from a firm's existing resource base, but from its capacity to evolve through distinctive processes such as effective coordination, knowledge integration, organizational learning, strategic reconfiguration, and innovation. These processes are shaped by the firm's asset base, including intangible assets like proprietary knowledge and organizational culture, and by its historical development paths (path dependency). Such evolutionary trajectories determine how firms adapt to change, with some enhancing and others constraining future strategic options. In environments characterized by increasing returns and technological disruption, firms that continuously refine their technological, managerial, and organizational capabilities are more likely to create and sustain value (Cavusgil & Deligonul, 2025). The adoption of artificial intelligence can thus be viewed as a manifestation of these dynamic capabilities, enabling firms to strengthen digital competencies and improve coordination across complex ecosystems, potentially extending to environmental, social, and governance dimensions as well.

DOI: 10.34659/eis.2025.95.4.1170

Methodology

Methods

This exploratory study employs a Rapid Literature Review (RLR) methodology (Barends et al., 2020; Grant & Booth, 2009; Harker & Kleijnen, 2012; Tricco et al., 2015) to investigate the evolving body of research on the relationship between corporate ESG performance and organizational AI deployment. RLRs have increasingly been recognized as efficient and practical methods for synthesizing existing evidence, particularly in time-sensitive situations where practitioners and policymakers require timely guidance, most notably within the healthcare sector (Khangura et al., 2012).

The Cochrane Collaboration, an international authority on systematic reviews, has significantly contributed to the development of rapid review methodologies. In 2020, its Rapid Reviews Methods Group released interim guidance that provides a structured approach to conducting rapid reviews across a range of disciplines, expanding beyond Cochrane's original health-focused mandate (Garritty, 2024). Although initially designed for urgent, health-related research, this approach has also been applied in scoping exercises to map evidence in newly emerging areas (Hamel et al., 2020; Smela et al., 2023).

Rapid reviews are purposefully structured to accelerate the process of synthesizing evidence by first screening peer-reviewed sources and then conducting a focused content analysis to critically evaluate the findings (Garritty, 2024). The methodology has demonstrated strong adaptability to fields such as business, management, industrial planning, and manufacturing (Jahangirian et al., 2011). The Center for Evidence-Based Management (CEBMa) has further refined this approach for use in organizational and managerial contexts, highlighting its value in producing timely, evidence-based insights to inform strategic decision-making (Barends et al., 2020). This flexibility underscores the broader relevance of the RLR approach for addressing complex and fast-changing challenges in management science. In particular, the RLR provides a practical and structured means to establish a foundational evidence base in emerging domains – essential for identifying key drivers, assessing impacts, and outlining potential strategic responses.

In addition to the Rapid Literature Review method, a snowball sampling technique was employed to broaden the scope of the review, in line with Wohlin's (2014) recommendations. This strategy enabled the inclusion of influential research not captured in primary academic databases, such as highly cited publications. To ensure a coherent and insightful synthesis of the findings, both focused content analysis and narrative analysis were conducted, allowing the results to be grouped thematically and synthesized narratively. This combined methodological approach facilitated a comprehensive and nuanced examination of the relationship between AI implementation and corporate ESG performance.

Sample

The Rapid Literature Review (RLR) was initiated on January 31, 2025, through a search of two major academic databases: Web of Science (WoS) and Scopus. In WoS, the search utilized the keywords "AI" AND "ESG" AND "ESG Performance" within the "All Fields" category, encompassing titles, abstracts, author keywords, and additional metadata. For Scopus, the search string applied was TITLE-ABS-KEY (AI) AND TITLE-ABS-KEY (ESG) OR TITLE-ABS-KEY (PERFORMANCE).

The multi-stage search and screening process followed a transparent rapid review protocol. A detailed overview of each stage, including database searches, inclusion and exclusion criteria, and quality appraisal procedures, is provided in Figure 1. The selection process was carried out in multiple stages. Searches were limited to peer-reviewed journal articles published in English and within the subject area of Business, Management, and Accounting. The initial query retrieved 21 records from WoS and 13 from Scopus, resulting in a combined total of 34 articles. After the removal of three duplicates identified across both databases, 31 unique studies remained for the initial screening stage.

To address the limited number of studies identified through database searches, a snowball sampling technique was applied using Google Scholar on February 14 and again on February 28, 2025. This process resulted in the identification of nine additional articles, bringing the total number of studies included in the initial screening to 40. The screening phase involved a systematic review of the titles, abstracts, and keywords to assess their relevance to the research focus. Following this step, the dataset was narrowed to 15 articles from Web of Science, 7 from Scopus, and 7 from Google Scholar, resulting in a combined total of 28 papers.

The review process, including study identification, screening, and data extraction, was performed by one researcher. To enhance consistency and reduce potential bias, clear inclusion and exclusion criteria as well as a standardized extraction protocol were applied throughout the process. Studies were excluded if they examined AI tools in which ESG was used only as a trial proxy, if AI was applied solely for the purpose of technically calculating ESG scores, if AI was analyzed alongside other technologies without isolating its independent effects, or if the research focus was entirely unrelated (e.g., studies involving electrosurgical generators). Notably, although the search was not restricted by geographical scope, all empirical studies included in the final dataset focused exclusively on the Chinese market. This first screening phase yielded 24 studies deemed suitable for further in-depth analysis.

Identification (31 January 2025)
Databases: Web of Science (WoS) & Scopus

- Search terms: "AI" AND "ESG" AND "ESG Performance"
- Filters: Peer-reviewed, English, Business/Management/Accounting
- Years covered: All years
- Countries of publication: All countries
- Results: WoS (21 articles, 2021–2024); Scopus (13 articles)
- Duplicates removed: 3 → 31 unique articles

Inclusion Criteria

- Peer-reviewed journal articles in English
- Business, Management & Accounting subject area
- Direct focus on AI and ESG performance

Exclusion Criteria

- ESG used only as a proxy or secondary topic
- AI used only to compute ESG scores
- AI analyzed jointly with other technologies (non-isolated)
- Non-relevant domains (e.g., electrosurgical generators)

Screening & Eligibility

- Title/abstract/keyword screening → 14 WoS + 7 Scopus = 21 retained
- Full-text analysis → 1 excluded (non-relevant domain)
- → 13 studies included

Supplementary Search (Snowballing)
Database: Google Scholar (14 & 28 February 2025)

- Additional 15 papers identified based on the same
- inclusion and exclusion criteria as for WoS and Scopus
- → Final dataset: 28 studies

Quality Appraisal

- 2023 SCImago Journal Rank (SJR): Q1–Q3
  13 Q1 | 4 Q2 | 3 Q3
- → 20 studies included

Final Sample

- 20 studies included for full content analysis
- Publication years: 2023–2025 (majority 2024)
- All empirical studies focused on Chinese marketComprehensive multi-stage RLR across WoS, Scopus, and Google Scholar

Figure 1. Rapid Literature Review (RLR) Protocol

DOI: 10.34659/eis.2025.95.4.1170

Another exclusion criterion, also serving as a proxy for study quality, was applied based on the 2023 SCImago Journal Rank (SJR) quartile classification to ensure the academic rigor of the selected studies. As a result, the dataset comprised articles published in Q1 and Q2 journals, along with three highly cited Q3 articles included to capture influential contributions beyond top-tier outlets. Specifically, the final selection encompassed thirteen articles from Q1 journals, four from Q2 journals, and three from Q3 journals. The complete list of journals represented in the review is provided in Table 1.

To further enhance methodological transparency, the selected empirical studies underwent an additional quality appraisal. The results are presented in a concise appraisal matrix provided as a supplementary table (Table A1 in Appendix 1). The matrix evaluates five key dimensions: (1) AI operationalization, (2) ESG operationalization, (3) research design, (4) research method, and (5) endogeneity and heterogeneity controls. This pragmatic approach was implemented to strengthen transparency while maintaining alignment with the streamlined nature of a Rapid Literature Review. Overall, the reviewed studies exhibit clearly defined constructs and robust empirical designs, with most incorporating explicit tests for endogeneity and heterogeneity.

Following the application of all inclusion and exclusion criteria, a full-text review was conducted. During this phase, one more article was excluded due to a lack of relevance, resulting in a final sample of 20 articles for in-depth analysis.

Table 1. Journal Distribution of Analyzed Papers by 2023 SCImago Quartile Ranking

Journal Title	2023 SJR Quartile (Q)	No of Papers Analyzed
Business Strategy and the Environment	Q1	1
Chinese Management Studies	Q3	1
Economic Analysis and Policy	Q1	1
Energy Economics	Q1	2
Finance Research Letters	Q1	2
International Journal of Innovation Management	Q2	1
International Review of Economics & Finance	Q1	1
International Review of Financial Analysis	Q1	1
Journal of Cleaner Production	Q1	1
Sustainable Development	Q1	2
Systems	Q2	1
Applied Economics Letters	Q3	1
International Review of Financial Analysis	Q1	1
Energy & Environment	Q3	1
Sustainability	Q2	2
Scientific Reports	Q1	1
	Total	**20**

Source: author's work based on selected journals.

Notably, the search strategy did not impose any restrictions on the year of publication in order to capture the full scope of available literature. However, all retrieved studies were published in 2023, 2024, or early 2025, underscoring the recent emergence of academic interest in the application of AI to corporate ESG performance (see Figure 2). This outcome reflects the nascent nature of the research area, with 2023 representing the earliest point at which scholarly discussions on leveraging AI for ESG enhancement began to appear in the academic literature.

DOI: 10.34659/eis.2025.95.4.1170

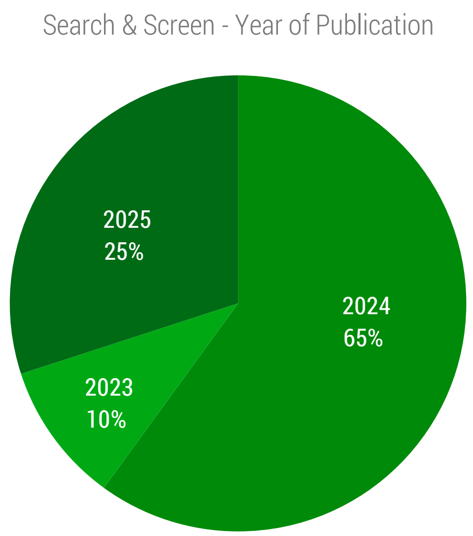

Figure 2. Distribution of Publications by Year
Source: author's work based on selected journals.

In summary, although the final search yielded a limited sample of 20 relevant peer-reviewed articles and was conducted by a single researcher, the triangulated approach – comprising searches across three databases at three distinct time points and restricted to studies that applied rigorous research procedures and underwent peer review in high-quality journals -ensured a comprehensive and methodologically robust review. This multi-step and transparent process enhanced the rigor, validity, and reliability of the findings, providing a solid foundation for analyzing the current state of research on the relationship between AI deployment and ESG performance at the firm level.

Research results

The body of research examining the relationship between the adoption of artificial intelligence and corporate ESG performance reveals several consistent trends and key insights (see Table 2). Among the twenty studies included in the full-content review – eighteen of which are empirical – the findings consistently demonstrate a significant positive relationship between AI implementation and improvements in firm-level ESG outcomes. This positive relationship is observed across diverse firm types, industry sectors, ownership structures, and regional contexts, underscoring the broad applicability of AI as a catalyst for enhancing corporate sustainability performance. The reviewed studies identify multiple mechanisms through which AI contributes to improved ESG outcomes, as well as mediating and moderating factors that shape this relationship. These findings are summarized in Figure 3 (Parts A and B) as a mind map manually created using the MindMeister application, which provides a structured visual overview of the key themes and categories emerging from the analysis.

Notably, all 18 empirical studies reviewed focus exclusively on Chinese listed companies, reflecting the impact of recent AI pilot policies and national digital governance strategies. The predominant focus of these studies is micro-level, with particular attention paid to firm-specific factors such as internal governance mechanisms, innovation capabilities, and digital infrastructure.

Among the most frequently cited mechanisms is data processing and information governance, where AI facilitates greater transparency, information sharing, and the reduction of information asymmetry (e.g., Zhou et al., 2025). Another mechanism involves innovation and R&D, with AI supporting corporate innovation capacity and the development of green technologies (e.g., He, 2024; Huang et al., 2024). AI is also instrumental in greenwashing mitigation, as it enables the detection and prevention of misleading sustainability claims (e.g., Li, et al., 2024; Zhang, 2024). Furthermore, AI contributes to digital transformation, which in turn positively moderates ESG outcomes (e.g., Liu et al., 2024; Xie & Wu, 2025) and promotes supply chain optimization by increasing efficiency and transparency (e.g., Lin & Zhu, 2024; S. Wang & Zhang, 2024). In addition, improvements in internal control and operational efficiency, facilitated by AI, are also linked to better ESG performance (e.g., Li et al., 2024).

Beyond these mechanisms, several studies point to variables that moderate the AI – corporate ESG performance relationship. Ownership structure appears to play a role, with private and non-state-owned enterprises often exhibiting stronger positive effects, although findings in this area remain inconclusive. Firm size is another factor, with medium and large enterprises generally benefiting more from AI-driven ESG enhancements than smaller firms. Regional disparities also emerge, as companies located in eastern and central China tend to experience greater ESG improvements compared to those in the western and northeastern regions.

DOI: 10.34659/eis.2025.95.4.1170

Table 2. Summary of Research Evidence Linking AI Adoption to Corporate ESG Performance

No	Authors	Research Focus	Study Design	2023 SCImago Quartile	Positive Relationship between AI and Corporate ESG Performance	Mediators of the Positive AI–ESG Relationship	Market Focus	Reported Neutral or Negative Effects of AI on Corporate ESG Performance	Level of Analysis
1	Chen et al., 2024	Enhancing ESG performance via AI: A firm-level analysis	empirical	Q1	AI improves ESG performance	Policy uncertainty reinforcing AI–ESG effect	China (listed firms)	n.a.	Micro (firm-level)
2	Chen & Zhang, 2024	How AI adoption affects ESG performance in enterprises	empirical	Q3	AI in firms has positive ESG impact	Governance, compliance, and information flow	China (listed firms)	n.a.	Micro (firm-level)
3	He, 2024	AI-driven ESG performance as a driver of innovation	empirical	Q2	AI enhances innovation capacity via ESG	AI adoption and digital transformation	China (listed firms)	n.a.	Micro (firm-level, innovation focus)
4	Huang et al., 2024	China's 2019 AIPZ policy effects on enterprise ESG performance	empirical	Q1	China AIP policy boosts ESG outcomes	Region, ownership, pollution & green innovation	China (listed firms)	n.a.	Micro (firm-level)
5	Jing & Zhang, 2024	AI and ESG outcomes in manufacturing firms	empirical	Q2	AI boosts ESG in manufacturing firms	Green innovation and firm size	China (listed firms)	n.a.	Micro (manufacturing firms)
6	Li et al., 2024	AI's role in reducing greenwashing and improving ESG	empirical	Q1	AI reduces greenwashing and agency issues	Politics, gender, and equity incentives	China (listed firms)	n.a.	Micro (firm-level, greenwashing)
7	Lin & Zhu, 2024	China's 2019 AIP policy and its impact on ESG ratings	empirical	Q1	China AIP policy improves supply chain ESG	Ownership, energy use, and sector type	China (listed firms)	High energy consumption	Meso (supply chain level)
8	Liu et al., 2024	AI's impact on ESG via R&D and digital transformation	empirical	Q1	AI increases R&D and digital transformation	Location and digital financial inclusion	China (listed firms)	n.a.	Meso (supply chain level)
9	Sætra, 2023	AI ESG Protocol: A tool for evaluating ESG outcomes	theoretical	Q1	n.a.	Firm AI/data capabilities	International	n.a.	Meso (AI-based governance frameworks)
10	Wang et al., 2024	AI for decarbonization in manufacturing: ESG impact	empirical	Q1	AI reduces carbon via production innovation	Size, profitability, ownership, and pollution level	China (listed firms)	n.a.	Micro (manufacturing firms)
11	Wang & Zhang, 2024	Generative AI and ESG performance in digital supply chains	empirical	Q1	Generative AI enhances digital supply ESG	Customer involvement in digital supply chains	China (tourism SMEs)	n.a.	Meso (digital supply chains)
12	Zhang & Yang, 2024	AI adoption and its influence on ESG performance	empirical	Q1	AI boosts ESG, limited governance effect	Absorptive capacity and industry type	China (listed firms)	Limited effect on governance performance	Micro (firm-level)

DOI: 10.34659/eis.2025.95.4.1170

No	Authors	Research Focus	Study Design	2023 SCImago Quartile	Positive Relationship between AI and Corporate ESG Performance	Mediators of the Positive AI–ESG Relationship	Market Focus	Reported Neutral or Negative Effects of AI on Corporate ESG Performance	Level of Analysis
13	Zhang, 2024	AI, greenwashing reduction, and ESG performance	empirical	Q1	AI reduces greenwashing via disclosure and innovation	Ownership, pollution, regulation, and regional development	China (listed firms)	n.a.	Micro (firm-level, greenwashing)
14	Chen & Ge, 2025	General impact of AI on ESG performance	empirical	Q3	AI elevates corporate ESG performance	Efficiency, human capital, digitalization, localization	China (listed firms)	n.a.	Micro (firm-level)
15	Li et al., 2025	How AI capabilities affect ESG outcomes	empirical	Q1	AI capabilities strengthen ESG	Resilience, innovation, and context factors	China (listed firms)	ESG impact depends on tailored AI use	Micro (firm-level)
16	Li et al., 2024	AI adoption's role in shaping firm ESG performance	empirical	Q3	AI improves ESG via financing and control	Ownership and centralization	China (listed firms)	n.a.	Micro (firm-level)
17	Saxena et al., 2023	Industry 4.0 technologies supporting ESG data	theoretical	Q2	AI improves ESG data and reporting	n.a.	International	n.a.	Macro–Micro (consumers & firms)
18	Xiao & Xiao, 2025	AI-driven ESG and sustainable development in SOEs	empirical	Q1	AI supports ESG in state-owned enterprises	ESG as intermediary between AI and SDGs	China (central SOEs)	n.a.	Micro, of a firm
19	Xie & Wu, 2025	Corporate ESG impact of AI technology adoption	empirical	Q2	AI application enhances corporate ESG	Digitalization, industry, location, and size	China (listed firms)	AI weakens internal controls leading to poor governance	Micro (firm-level)
20	Zhou et al., 2025	AI's contribution to improved ESG outcomes	empirical	Q1	AI improves ESG performance	Corporate information governance and ownership	China (listed firms)	n.a.	Micro (firm-level)

Notes: n.a. = not assessed in the study/ not applicable
Source: author's work based on reviewed literature.

DOI: 10.34659/eis.2025.95.4.1170

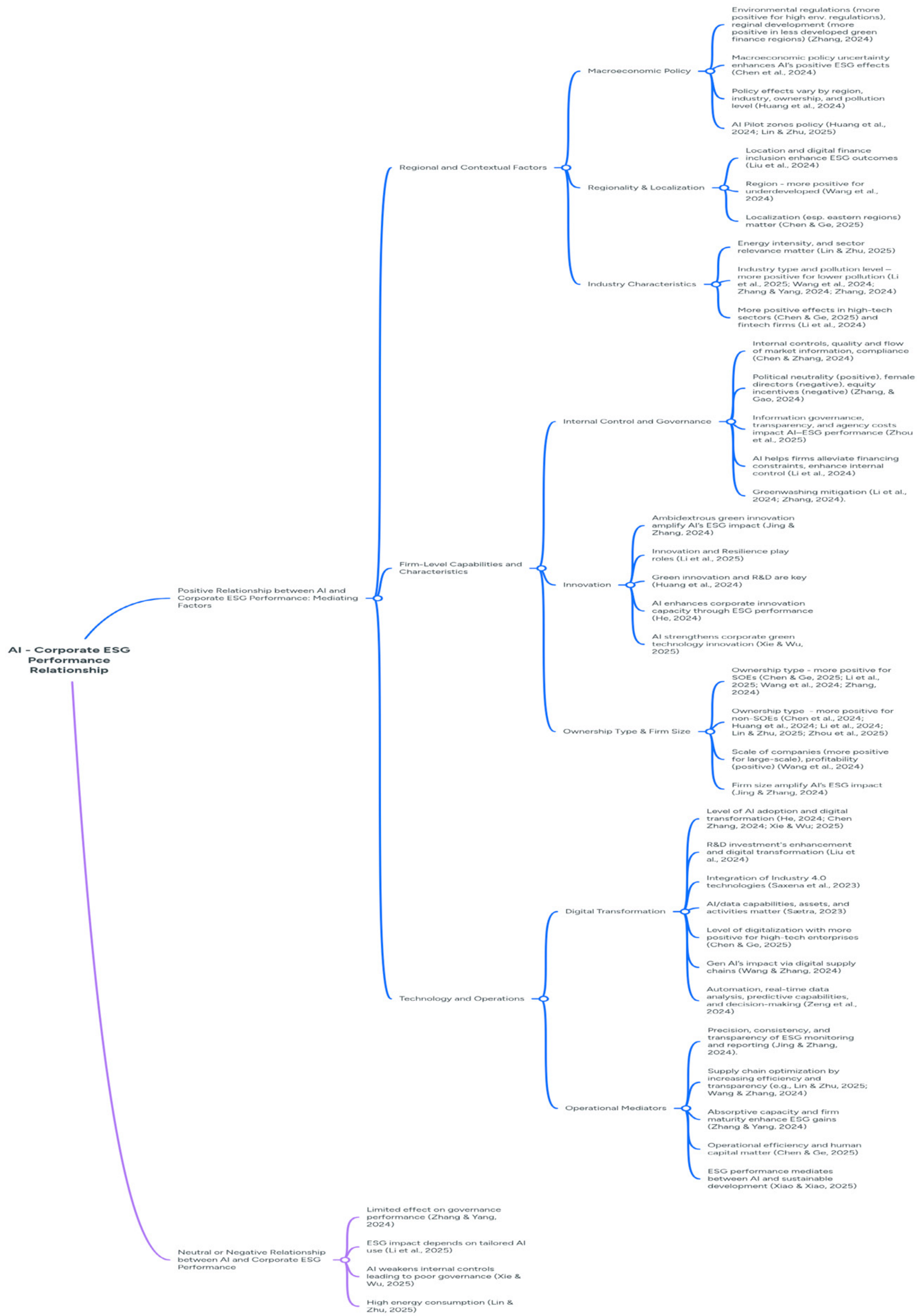

Figure 3. Factors Mediating and Moderating the AI–Corporate ESG Performance Relationship – Part A

Source: author's work based on literature synthesis using MindMeister app, https://www.mindmeister.com

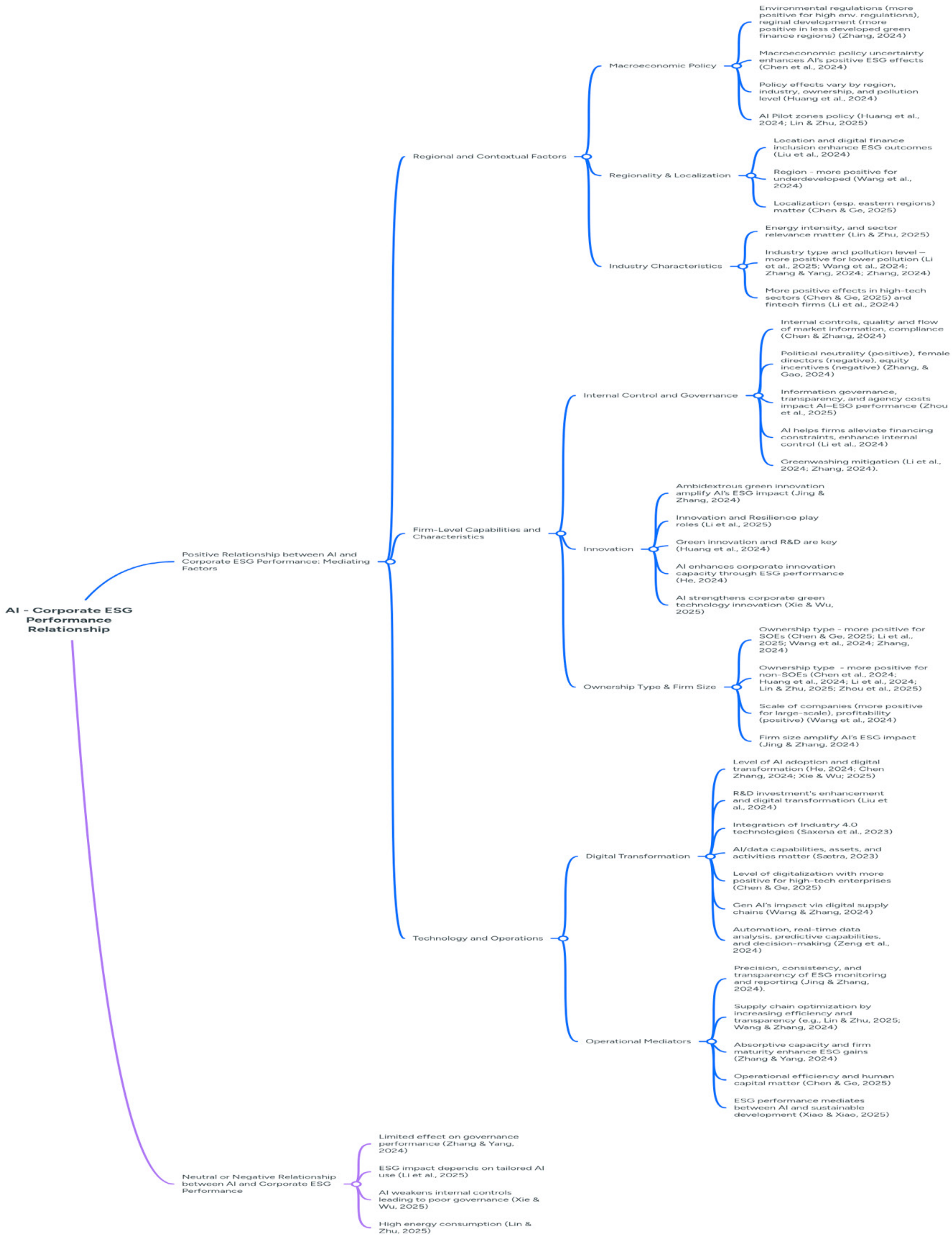

Figure 3. Factors Mediating and Moderating the AI–Corporate ESG Performance Relationship – Part B

Source: author's work based on literature synthesis using MindMeister app, https://www.mindmeister.com

Lastly, industry competitiveness influences outcomes, with AI showing a more pronounced effect in sectors that are highly competitive and technologically intensive.

Although most studies emphasize the positive impact of artificial intelligence on corporate ESG performance, relatively few examine its potential drawbacks. Among the studies addressing negative implications, several highlight governance-related concerns (Zhang & Yang, 2024; Xie & Wu, 2025) and note that the effectiveness of AI in advancing ESG objectives depends on context-specific implementation strategies (Li et al., 2025). Beyond governance challenges, the substantial energy consumption associated with AI technologies raises critical questions about the environmental sustainability of AI itself (Lin & Zhu, 2024).

Finally, theoretical contributions by Sætra (2023) and Saxena et al. (2023) further enrich the discourse. Sætra (2023) introduces a flexible AI-ESG protocol intended to guide ethical and context-sensitive implementation, while Saxena et al. (2023) explore the role of Industry 4.0 technologies and AI in enhancing ESG data infrastructure and transparency. Collectively, these insights underscore the importance of a nuanced and critical perspective when evaluating the role of AI in ESG performance.

Discussion

As outlined in the Research Results section, the review findings strongly support a positive relationship between the deployment of artificial intelligence and enhanced corporate ESG performance. The integration of artificial intelligence technologies presents considerable potential to advance organizational ESG agendas by increasing operational efficiency, facilitating data-driven decision-making, and promoting the adoption of more sustainable practices.

At the same time, the Dynamic Capabilities Framework adopted in this study underscores that long-term organizational success depends on a firm's capabilities, specifically ability to learn, innovate, and adapt to environmental change (Teece et. al., 1997). Accordingly, the mechanisms through which AI enhances corporate ESG performance can be broadly categorized into three interrelated domains: firm-level capabilities and characteristics; technological and operational mediators; and regional and contextual factors.

Firm-level capabilities and characteristics shaping the AI–ESG relationship

Firm-level capabilities serve as key mediators in the relationship between artificial intelligence adoption and ESG performance, particularly in shaping corporate governance practices. AI-driven improvements in oversight and managerial control play a pivotal role in amplifying these outcomes. By enhancing monitoring systems, alleviating financing constraints, and strengthening overall organizational performance, AI contributes to more effective and transparent ESG management (Li et al., 2024). It also supports ESG advancement by improving the efficiency of internal controls and enriching the quality and flow of market information (R. Chen & Zhang, 2024). Moreover, corporate compliance emerges as a critical moderating factor influencing the magnitude of AI's impact on ESG outcomes.

Further evidence from Zhou et al. (2025) identifies enhanced corporate information governance as a key mechanism linking AI adoption to improved ESG outcomes. This mechanism encompasses greater transparency, more effective information sharing, and reduced information asymmetry – all of which contribute to improved environmental disclosure, more efficient supply chain management, and lower agency costs. Collectively, these findings underscore the importance of robust internal governance controls, strong compliance systems, and an integrated information environment in maximizing the ESG value of AI integration.

In contrast to the predominantly positive relationship between AI deployment and firm-level ESG performance through strengthened governance controls, Liu et al. (2024) identify a notable drawback – the implementation of AI technologies may weaken the effectiveness of internal control systems due to the automation of data sourcing and reduced human oversight, thereby diminishing governance performance. Their findings highlight the need for a balanced and cautious approach to AI integration to ensure that technological advancement does not compromise fundamental aspects of corporate governance.

Furthermore, Zhang and Yang (2024) find that although AI adoption significantly improves environmental and social performance, its impact on governance remains limited. Their study identifies absorptive capacity – defined as a firm's ability to acquire, assimilate, and apply external sustainability-related knowledge – as a key mediating mechanism in the relationship between AI adoption and firm-level ESG outcomes. The findings suggest that AI contributes to sustainability not only through direct technological advancements but also by enhancing firms' capacities to internalize and implement ESG-oriented practices. These positive effects of AI are more pronounced in mature firms relative to those at earlier stages of development and in non-polluting industries compared with more environmentally intensive sectors.

Complementing this view, Xie and Wu (2025) caution that although AI can generate notable improvements in environmental and social dimensions, its contribution to governance is less consistent and, in some cases, potentially adverse. AI adoption may undermine internal control systems, thereby diminishing governance quality. Taken together, this evidence underscores the complex nature of AI's influence on ESG performance, highlighting the importance of organizational capabilities, and governance safeguards in shaping outcomes.

While empirical research generally confirms a positive link between ESG performance and sustainable development, several challenges continue to impede the full realization of ESG's transformative potential. Key obstacles include the lack of standardized metrics, inconsistencies in data quality and disclosure, and the absence of robust regulatory frameworks to support meaningful ESG integration (Zhang, 2024). Among these, greenwashing remains a particularly pressing concern, as it undermines the credibility of sustainability initiatives and weakens their long-term impact (Zhang, 2024).

At the same time, AI adoption can play a pivotal role in mitigating greenwashing (Zhang, 2024; Li et al., 2024). Zhang (2024) demonstrates that AI improves the quality and transparency of ESG disclosures, particularly in environments with weaker external sustainability oversight, where its role in enhancing accountability is most pronounced. AI contributes to this outcome through multiple channels, including easing financial constraints, reducing managerial burdens related to ESG compliance, and fostering green innovation. These findings highlight the potential of AI as an effective governance instrument for promoting credible sustainability practices and strengthening the reliability of ESG reporting frameworks.

Moreover, AI mitigates greenwashing by alleviating agency problems, and enhancing external scrutiny (Li et al., 2024). The deterrent effect of AI is particularly evident in firms without political affiliations, those with lower female board representation, and those characterized by weaker equity-based incentives. Collectively, these findings underscore the potential of AI as an effective governance mechanism that enhances transparency and accountability in sustainability reporting, thereby improving the credibility of ESG disclosures and supporting the stability of capital markets.

Furthermore, AI applications significantly contribute to carbon reduction, primarily through innovations in production processes, technological advancements, and improved management practices (Wang et al., 2024). The research reports particularly strong effects among large, profitable, and state-owned enterprises. Integrating AI into manufacturing appears to improve ESG performance, especially across the environmental and governance dimensions. These advancements are largely driven by gains in total factor productivity, greater technological innovation, and higher transparency in information disclosure.

Despite the above benefits of artificial intelligence for enhancing firm-level ESG performance, a growing body of literature cautions that its deployment is accompanied by significant environmental trade-offs. Lin and Zhu (2024) emphasize that the rapid advancement and widespread adoption of AI technologies have substantially increase energy demand, potentially hindering progress toward sustainability targets. The training and operation of large-scale AI models require intensive computational resources, which translate into elevated electricity consumption and associated carbon emissions. These challenges underscore the importance of pursuing "green AI" strategies that mitigate environmental costs while preserving technological benefits.

At the same time, evidence suggests that AI can serve as a critical enabler of environmental stewardship. From an operational perspective, AI facilitates more precise monitoring of energy usage, the optimization of manufacturing processes, and the reduction of waste and emissions (Nishant et al., 2020; Vinuesa et al., 2020). Complementing this view, Xiao and Xiao (2025) find that central state-owned enterprises in China have successfully integrated AI into environmental management sys-

DOI: 10.34659/eis.2025.95.4.1170

tems, particularly in resource allocation and pollution control, resulting in reduced resource consumption, improved energy efficiency, and enhanced wastewater treatment.

Contrary to the perception that AI's environmental footprint negates its benefits, recent research has revealed a more nuanced dynamic. Chishti et al. (2024) show that although AI-driven operations have increased electricity consumption, they have simultaneously incentivized investment in cleaner energy alternatives. Industry initiatives such as Intel's Hala Point neuromorphic system exemplify how technological innovation can achieve breakthroughs in energy efficiency and performance, setting a new benchmark for the development of "green AI" (Huang et al., 2024). Similarly, Li et al. (2024) demonstrate that AI technologies can optimize resource utilization, improve energy-emissions management, and enhance decision-making precision, thereby improving firms' financial performance (ROA) and, in turn, their ESG outcomes. In aggregate, these findings indicate that while AI introduces new environmental challenges through its energy demands, it also offers powerful mechanisms for mitigating these impacts and fostering more sustainable, efficient, and transparent corporate practices.

Furthermore, literature reviewed points to a more complex, non-linear dynamic between AI and energy transition. Lee and Yan (2024) identify a U-shaped relationship, whereby AI adoption initially exerts a negative influence on the shift toward cleaner energy systems. Only after surpassing a certain threshold does AI begin to facilitate a meaningful transition to sustainable energy use. This nuanced relationship underscores the need for carefully crafted policy interventions to ensure that AI integration supports, rather than hinders, broader environmental and sustainability objectives.

Li et al. (2025) advance the discourse on technology-driven sustainability by examining how artificial intelligence enhances ESG performance through innovation-based pathways. Their study highlights key organizational enablers, particularly resilience and innovation capacity, as critical in mediating the AI–ESG relationship. Notably, organizational resilience is shown to amplify the positive effects of AI, especially within technology-intensive industries. The integration of AI technologies positively influences sustainable development practices, with ESG serving as a mediating mechanism that links AI adoption to enhanced corporate governance, environmental stewardship, and social responsibility.

In this context, it is noteworthy that the majority of the reviewed studies examine the moderating role of organizational ownership structures in shaping the relationship between AI adoption and corporate ESG performance; however, the findings remain mixed and inconclusive. While some studies suggest that state-owned enterprises (SOEs) are better positioned to leverage AI in pursuit of ESG objectives (e.g., Chen & Ge, 2025; Li et al., 2025), others indicate that the positive effects of AI adoption are more pronounced in privately owned or non-state-owned enterprises (non-SOEs), particularly those operating in environments characterized by lower levels of institutional scrutiny (e.g., Zhou et al., 2025; Lin & Zhu, 2024; Li et al., 2024; Huang et al., 2024; Chen et al., 2024).

In summary of the discussion on firm-level capabilities and characteristics shaping the AI–ESG relationship, it is valuable to introduce Sætra's (2023) AI ESG Protocol, which offers a structured framework for understanding how organizational AI and data-related resources translate into sustainability outcomes. Within this framework, *capabilities* refer to the competencies, tools, methodologies, and processes used in the development of AI systems and the collection of data – for example, a firm's expertise in algorithm design or its infrastructure for gathering sensor-based data. *Assets* encompass the organization's tangible AI-related resources, including proprietary algorithms, data systems, and curated datasets, such as in-house social media platforms or specialized data repositories. *Activities* describe the practical deployment of these capabilities and assets in ways that shape strategic direction, innovation, and market positioning. This may involve, for instance, product development processes where AI tools enable clients to harness their own data more effectively to optimize performance. Taken together, the AI ESG Protocol offers a comprehensive lens for assessing the sustainability implications of AI, bridging technological capabilities with responsible innovation. At the same time, organizational characteristics, such as human capital, absorptive capacity, firm maturity, and ownership structure, emerge as critical factors that condition the extent to which AI adoption translates into tangible sustainability benefits. These insights underscore that the integration of AI is not inherently transformative; rather, its effectiveness depends upon a firm's internal readiness and structural orientation (Sætra, 2023).

DOI: 10.34659/eis.2025.95.4.1170

Technological and operational mediators of AI – ESG performance

The second cluster of mediating factors underscores the pivotal role of technological maturity and operational efficiency in linking AI adoption to enhanced firm-level ESG performance. Variables such as the degree of AI integration into operational and sustainability-focused systems serve as key mediators, shaping ESG outcomes through functional and process-oriented pathways. Notably, advancements in energy efficiency, reductions in waste emissions, and the implementation of circular economy practices often depend on the availability of advanced technological capabilities (Chen & Xie, 2022). Chen and Ge (2025) emphasize that AI-driven improvements in operational efficiency and the optimization of human capital are critical channels through which ESG benefits are realized. Nevertheless, the complexity involved in collecting, processing, and analyzing ESG-related data remains a significant challenge for firms aiming to accurately evaluate and enhance their ESG performance.

Therefore, the advancement of AI technologies offers promising solutions to these challenges. AI is increasingly reshaping business operations and organizational workflows by facilitating automation, real-time data analysis, and predictive capabilities that enhance strategic decision-making (Lin & Zhu, 2024; Zeng et al., 2024). Moreover, AI improves the precision, consistency, and transparency of ESG monitoring and reporting by enabling advanced metric tracking and real-time access to performance insights (Jing & Zhang, 2024). Overall, AI adoption underscores the pivotal role of technological innovation in enhancing efficiency and fostering sustainable corporate practices (Li et al., 2024).

The integration of Industry 4.0 technologies, such as the Internet of Things (IoT), blockchain, big data, and artificial intelligence, offers transformative potential through capabilities including real-time data collection, data authentication, predictive analytics, transparency, and structured data management (Saxena et al., 2023). The adoption of these technologies can significantly enhance the acquisition and processing of ESG data, thereby improving the overall quality and reliability of ESG reporting and, consequently, ESG assessments.

As consumers increasingly demand accurate and verifiable ESG information, AI deployment may become a game-changer for many organizations that still struggle with inconsistent or manipulated disclosures. Chen and Zhang (2024) further suggest that AI-driven digital transformation can serve as a powerful mechanism for advancing the sustainable development agenda and facilitating the transformation and upgrading of the manufacturing sector in particular.

As such, AI functions as a critical enabler in strengthening corporate ESG performance and driving sustainable business transformation. Liu et al. (2024) find that AI adoption encourages increased investment in research and development, as well as deeper digital transformation, both of which contribute positively to ESG outcomes. Complementing these findings, Xie and Wu (2025) demonstrate that the degree of corporate digitalization significantly moderates the relationship between AI adoption and ESG performance. Their channel analysis reveals that AI enhances the environmental (E) dimension by fostering green technological innovation and improves the social (S) dimension through greater corporate engagement in philanthropic activities. These two components – environmental innovation and social responsibility – emerge as the primary drivers behind the observed improvements in overall ESG performance.

In addition to the above efficiency gains, recent research emphasizes the emerging role of generative AI in advancing corporate sustainability objectives. Wang and Zhang (2024) investigate this area and find that generative AI positively moderates the relationship between digital supply chain integration and ESG performance, with customer involvement acting as a key enabling factor. Simultaneously, generative AI strengthens firms' innovation capacity and supports more effective collaboration within digitally integrated supply chains.

Moreover, both ESG performance assessment and research on the impacts of AI face ongoing challenges related to the lack of standardization (e.g., Chen et al., 2024; Lin & Xu, 2024). This is particularly evident in the absence of consistent ESG measurement criteria, evaluation metrics, rating systems, and reporting frameworks, which hinders the comparability and reliability of findings across contexts.

In response to the need for greater conceptual clarity, He (2024) adopts a reverse analytical perspective by investigating how ESG performance influences corporate innovation capabilities, with artificial intelligence adoption and digital transformation serving as mediating variables. The study

DOI: 10.34659/eis.2025.95.4.1170

provides robust empirical evidence that strong ESG performance significantly enhances a firm's innovation capacity, primarily through increased AI integration and more advanced digital infrastructure. These findings offer valuable insights into the mechanisms by which sustainability-oriented strategies can stimulate technological innovation. Importantly, the research highlights that ESG initiatives can serve not only as compliance tools but also as strategic assets that strengthen firms' competitive advantage in an increasingly digital and innovation-driven economy.

Building on this line of inquiry, Jing and Zhang (2024) develop a theoretical model that explores the influence of AI on firm-level ESG performance, focusing specifically on the mediating role of ambidextrous green innovation. Their findings indicate that AI adoption significantly improves ESG outcomes through two distinct innovation pathways: explorative and exploitative green innovation. The study further reveals that firms maintaining a balanced approach to both types of innovation, particularly larger enterprises, derive the greatest benefits from AI integration. A heterogeneity analysis confirms that the effectiveness of AI in enhancing ESG performance is contingent upon factors such as firm size and the degree of innovation balance. These results underscore the importance of aligning AI strategies with organizational and technological contexts and innovation capacities, particularly in sectors such as manufacturing, where tailored approaches are essential for maximizing sustainability outcomes.

Regional and contextual factors of AI's ESG effectiveness

The third and final cluster of mediating factors comprises regional and contextual variables, underscoring that geographical location, regulatory environments, and policy orientations are not neutral settings but active constituents shaping the relationship between AI adoption and corporate ESG performance.

The magnitude of corporate ESG benefits derived from AI deployment varies substantially across regions and sectors, reflecting differences in structural conditions, regulatory frameworks, and technological maturity (Lin & Zhu, 2025). Both industry characteristics and geographic context shape the degree to which AI contributes to firm-level ESG performance. Positive effects are especially evident in high-tech sectors (Chen & Ge, 2025) and fintech firms (Li et al., 2024), suggesting that technologically advanced industries are better positioned to capitalize on AI-driven ESG enhancements. Furthermore, firms located in specific regions, particularly those with more developed digital ecosystems, demonstrate stronger ESG performance linked to AI integration (Chen & Ge, 2025; Huang et al., 2024; Wang et al., 2024; Xie & Wu, 2025). Notably, Liu et al. (2024) observe that the positive impact of AI on ESG outcomes is significantly amplified in provinces characterized by higher levels of digital financial inclusion. These findings highlight the importance of accounting for regional and sectoral contexts when assessing the efficacy and equity of AI-enabled sustainability transitions.

In the context of Chinese firms operating within the domestic market, a particularly salient factor influencing the AI – corporate ESG performance relationship is the proactive national policy surrounding designated AI pilot zones, specifically, the National New Generation Artificial Intelligence Innovation and Development Pilot Zone initiated in 2017 (Department of International Cooperation Ministry of Science and Technology, P.R. China, 2017). These policy initiatives provide institutional support and strategic incentives that significantly enhance firms' ESG performance by facilitating the integration of advanced AI technologies. Huang et al. (2024) employ this pilot zone framework as a quasi-natural experiment to investigate the impact of AI-related policy interventions on corporate ESG outcomes. Their empirical findings demonstrate that the implementation of this policy leads to significant improvements in ESG performance. Heterogeneity analysis further reveals that the policy's effects are not uniform: they are more pronounced among firms located in certain regions (eastern and central China), in non-state-owned enterprises, and in industries characterized by high levels of pollution (Huang et al., 2024). Mechanism analysis identifies two critical pathways driving the improvements – green technological innovation and increased R&D investment – underscoring the strategic value of AI in enabling environmentally responsible and innovation-led business models.

Lin and Zhu (2024) examine the impact of another regulation – the China Artificial Intelligence Pilot (AIP) Policy, introduced in 2019 (State Council of the People's Republic of China, 2021), a successor to the National New Generation Artificial Intelligence Innovation and Development Pilot Zone – on corporate ESG performance. Their heterogeneity analysis reveals that the positive effects of the AIP policy are particularly pronounced among energy-intensive firms and those operating within the

DOI: 10.34659/eis.2025.95.4.1170

new energy sector. As the authors emphasize, strengthening ESG performance in energy-intensive industries is especially critical given their substantial energy consumption and significant environmental impact throughout the production process. In the Chinese context, the AIP policy supports these industries in upgrading toward higher value-added production by facilitating the adoption of AI technologies. Through AI integration, firms enhance supply chain management and operational efficiency, thereby achieving notable improvements in ESG outcomes. Simultaneously, the renewable energy sector, especially in wind and solar power, which play pivotal roles in combating climate change and advancing the energy transition, has experienced substantial gains in generation efficiency through AI deployment. Artificial intelligence demonstrates potential in improving power generation performance, reducing operational costs, and optimizing resource allocation. These advancements enable firms to better align with policy directives and pursue sustainable, low-carbon development paths. Overall, the findings underscore the potential of well-designed AI regulatory initiatives to drive sustainable business practices, especially in industries where environmental concerns are most acute. The study also highlights how targeted policy frameworks can catalyze AI adoption in ways that directly enhance ESG outcomes and support broader environmental and innovation-driven goals.

Furthermore, the positive relationship between AI and ESG performance is amplified in regions characterized by stricter environmental regulations and greater banking sector concentration (Li et al., 2024). This evidence highlights the critical role of government policy and institutional context in enabling digital transformation and promoting broader ESG objectives in emerging economies such as China.

In this context, Chen et al. (2024) demonstrate that macroeconomic policy uncertainty acts as a moderating variable, amplifying AI's positive influence on ESG outcomes. The study identifies two primary mechanisms through which AI enhances ESG performance: by increasing firms' total factor productivity and by stimulating research and development (R&D) investment. Moreover, the analysis reveals that AI exerts a particularly strong positive effect on the ESG performance of technology- and capital-intensive firms.

AI fosters ESG performance also through sector-specific characteristics, where regulatory environments shape the effectiveness of AI in promoting sustainability. Notably, the impact of AI on ESG performance is industry dependent. The positive effects of AI adoption on ESG outcomes are more pronounced both among less polluting firms (Li et al., 2025; Wang et al., 2024; Zhang, 2024) and among those operating in heavily polluting industries (Huang et al., 2024). Xie and Wu (2025) further show that the positive influence of AI on ESG performance is stronger in competitive and technology-intensive sectors. In addition, large- and medium-sized enterprises demonstrate greater improvements compared to smaller firms, with medium-sized firms exhibiting particularly strong potential for further progress and thus achieving a higher marginal effect relative to large firms.

Managerial and policy recommendations

The reviewed studies demonstrate that artificial intelligence can substantially enhance firm-level environmental, social, and governance performance, yet its effects are not uniformly positive. Managers and policymakers should therefore adopt a balanced, context-sensitive approach that maximizes benefits while mitigating potential risks.

Key managerial recommendations for integrating AI to improve firm-level ESG performance include:

- **Integrate AI into ESG strategy -** embed AI capabilities within corporate sustainability planning to strengthen data-driven management, support informed decision-making, and improve overall ESG outcomes.
- **Strengthen governance and accountability** – establish robust AI accountability frameworks with transparent model documentation, audit trails, and independent oversight of AI-driven decisions to mitigate opacity risks and reinforce governance controls.
- **Embed ethical and digital competence in governance** – incorporate ethical AI principles into corporate governance codes to oversee responsible AI adoption.
- **Stimulate innovation and efficiency –** use AI to enhance R&D capacity, accelerate the development of green technologies, and reduce carbon emissions through process optimization.

DOI: 10.34659/eis.2025.95.4.1170

- **Enhance transparency and credibility** – leverage AI tools to strengthen data accuracy, improve the quality and auditability of ESG disclosures, and mitigate the risk of greenwashing.
- **Optimize supply-chain management** – apply AI solutions to increase traceability, improve supplier assessment, and monitor ESG-related data and risks throughout the supply chain.
- **Strengthen sustainable organizational management practices –** utilize AI to enhance operational efficiency and data accessibility, thereby improving eligibility for ESG-linked financing and aligning strategic and investment decisions with sustainability objectives.

Key cautionary considerations encompass:

- While AI-based analytics strengthen monitoring, fraud detection, and compliance processes, others suggest that automation and algorithmic decision-making can weaken managerial accountability or introduce new opacity risks.
- Governance impact may be limited – evidence indicates that AI's positive effects are generally stronger for environmental and social dimensions than for governance outcomes. Without proper oversight, AI adoption may undermine governance quality and heighten operational or ethical risks.
- Effectiveness depends on tailored implementation – the ESG benefits of AI vary across sectors and depend on how technologies are integrated into existing organizational systems.

For policymakers and regulators, the literature suggests several recommendations to amplify the positive influence of AI on firm-level ESG outcomes, including, but not limited to, the following:

- Formulating region – and sector-specific policy frameworks that support ESG-driven initiatives leveraging AI technologies as key enablers.
- Establishing innovation support platforms that connect AI solution providers with corporate ESG initiatives, projects, and programs.
- Promoting sustained R&D investment at the firm level to advance the development of AI-enabled ESG solutions.
- Developing comprehensive monitoring and evaluation systems to mitigate AI-related risks in the ESG context and prioritize investments that deliver measurable improvements in firm-level ESG performance.
- Encouraging the wider adoption of AI technologies for smart grid optimization and renewable energy integration, which have already demonstrated significant efficiency gains and reductions in carbon emissions.

Both managers and regulators should therefore accompany AI deployment with robust data governance frameworks, ethical oversight, and continuous monitoring to ensure that technological innovation reinforces, rather than undermines, firm-level ESG outcomes, corporate governance, and organizational accountability.

Limitations and future research agenda

Despite promising findings, the scope of existing research remains geographically narrow, even though the RLR protocol did not restrict studies by country or market. All empirical evidence identified in this review originates from Chinese firms listed on domestic stock exchanges, reflecting both the availability of firm-level ESG data and China's policy emphasis on AI-driven digital transformation. While this body of work provides a valuable foundation, it also introduces potential geographical bias. Some scholars argue that these results may hold relevance beyond China (e.g., Chen & Zhang, 2024), yet such claims remain largely speculative in the absence of comparative, cross-country evidence.

This geographical concentration limits the external validity and generalizability of current conclusions. Institutional differences, such as regulatory frameworks, corporate governance systems, and levels of digital maturity, can substantially influence both AI adoption and ESG performance. For instance, China's strong state involvement in AI policy and data governance contrasts with the more decentralized and market-oriented approaches observed in Europe or North America. Future research should therefore seek to validate and extend these findings through multi-regional or comparative analyses, thereby advancing a more globally representative understanding of the firm-level

DOI: 10.34659/eis.2025.95.4.1170

AI–ESG performance nexus and informing the formulation of internationally relevant policy recommendations.

Furthermore, several additional limitations should be acknowledged. First, the research field is still in its early stages, with most empirical studies published only since 2023, resulting in a limited empirical base. Second, conceptual ambiguity persists, as the construct of ESG performance lacks a unified definition across studies. In some cases, it is operationalized as a proxy for overall sustainability or SDG alignment, whereas in others it is equated with ESG ratings without sufficient methodological justification, often relying on publicly available indicators such as the Sino-Securities Index ESG Ratings or the Huazheng ESG Index as direct measures of ESG performance.

To address these limitations, future research should prioritize cross-indicator and cross-national empirical analyses, particularly comparing European, U.S., and other global markets. This would allow for a more robust examination of AI–ESG relationships within varied institutional and regulatory contexts, especially in light of recent legislative developments such as the European Union's *Artificial Intelligence Act* (European Parliament and Council, 2024) or the United States' *The National Artificial Intelligence Research and Development Strategic Plan* (United States National Science and Technology Council, 2016). Additionally, greater attention could be paid to the role of external factors such as non-financial reporting regulations and sustainability disclosure directives, particularly in the context of the European Union, where such frameworks have already been introduced (e.g., European Commission, 2020; European Parliament and Council, 2022).

Moreover, although AI applications may enhance firms' environmental performance, their own energy and emissions footprints remain largely unexamined. Training large models and operating data centers can significantly increase electricity consumption, raising questions about the net carbon effect of AI adoption. Future studies should quantify these trade-offs and integrate them into firm-level ESG assessments to explore how differences in digital infrastructure, energy mix, and regulatory context influence the balance between AI's environmental benefits and costs.

Furthermore, as the impact of AI may vary significantly across the environmental (E), social (S), and governance (G) components, future studies should more explicitly differentiate among the three dimensions of ESG in the context of AI deployment. A more granular exploration of how AI affects each pillar would contribute to a clearer understanding of its role in shaping corporate sustainability strategies.

Future research should further explore the complex relationship between AI deployment and corporate governance outcomes, as empirical evidence on this link remains mixed. While several studies suggest that AI-based analytics enhance monitoring, fraud detection, and compliance processes, others indicate that automation and algorithmic decision-making may weaken managerial accountability or introduce new forms of opacity. These divergent findings point to the importance of identifying boundary conditions that moderate AI's governance effects. Specifically, future studies should examine how organizational maturity and data governance capacity determine whether AI strengthens or substitutes for traditional oversight mechanisms. Similarly, regulatory context and board-level digital literacy are likely to influence the extent to which AI tools are implemented responsibly and transparently. Finally, firm size and ownership structure may condition how effectively AI-driven controls align with broader corporate governance goals. Empirical research should aim to develop theoretical and quantitative models that capture when and how AI enhances, rather than undermines, the quality of internal controls and governance integrity.

Lastly, since the empirical studies reviewed in this article were predominantly quantitative, the field would benefit from more qualitative research, such as in-depth interviews with managers and practitioners directly involved in corporate AI implementation. These approaches could offer deeper insights into the decision-making processes and contextual dynamics that influence the relationship between AI and ESG performance at the firm level.

DOI: 10.34659/eis.2025.95.4.1170

Conclusion

This study contributes to the growing body of research on the firm-level nexus between artificial intelligence adoption and corporate ESG performance, highlighting how technological innovation reshapes sustainability practices. The integration and advancement of AI technologies offer significant opportunities for improving corporate performance across environmental, social, and governance dimensions. Through advanced data mining, real-time analytics, and optimized resource allocation, AI functions as a critical enabler of sustainable and responsible business practices. By enhancing operational efficiency and decision-making capacity, AI facilitates the transition toward data-driven sustainability strategies that strengthen firms' long-term competitiveness and accountability.

The findings reveal a predominantly positive relationship between AI adoption and firm-level ESG performance, as consistently reported across the reviewed literature. However, the magnitude and nature of this relationship vary based on several moderating factors, which can be broadly categorized into three interrelated domains: (1) firm-level capabilities and characteristics, (2) technological and operational mediators, and (3) regional or contextual factors. Among the most frequently cited mechanisms is the role of AI in strengthening information governance – facilitating greater transparency, improving data sharing, and reducing information asymmetry. AI also enhances corporate innovation capacity through support for R&D and the development of green technologies. Furthermore, it plays a pivotal role in detecting and mitigating greenwashing by ensuring more accurate and trustworthy ESG reporting.

In addition, AI contributes significantly to digital transformation, which in turn moderates ESG outcomes by increasing adaptability, responsiveness, and integration across business operations. Supply chain optimization is one of such areas where AI proves beneficial, improving transparency and efficiency across production and distribution networks. Enhanced internal control systems and gains in operational efficiency further strengthen ESG performance, particularly when AI tools are tailored to the firm's context.

Several studies highlight contextual factors moderating the AI–ESG relationship, including ownership structure, firm size, regional context, and industry competitiveness, although findings remain mixed. While AI generally enhances ESG performance, some studies raise concerns about limited governance benefits, weakened internal controls, and the environmental cost of energy-intensive AI technologies. Ultimately, the effectiveness of AI depends on context-specific implementation and a strategic firm's capabilities.

In conclusion, this body of research contributes to the further development of the AI –ESG performance nexus, offering practical insights for managers, policymakers, and regulators seeking to foster sustainable development at the firm level. Collectively, the synthesized findings provide a foundation for broader, more inclusive, and empirically grounded investigations into the transformative potential of AI in promoting sustainable corporate practices.

References

Acemoglu, D., & Restrepo, P. (2018). The Race between Man and Machine: Implications of Technology for Growth, Factor Shares, and Employment. American Economic Review, 108(6), 1488–1542. https://doi.org/10.1257/aer.20160696

Ahmed, N., Wahed, M., & Thompson, N. C. (2023). The growing influence of industry in AI research. Science, 379(6635), 884–886. https://doi.org/10.1126/science.ade2420

Ayming. (2025). Międzynarodowy bartometr ESG 2025. Wdrożenie ESG i zgodność z dyrektywą CSRD: gdzie aktualnie jest Twoja firma? https://www.ayming.pl/analizy-i-aktualnosci/raporty/miedzynarodowy-barometr-esg-2025/ (in Polish).

Babina, T., Fedyk, A., He, A., & Hodson, J. (2024). Artificial intelligence, firm growth, and product innovation. Journal of Financial Economics, 151, 103745. https://doi.org/10.1016/j.jfineco.2023.103745

Barends, E., Rousseau, D.M. & Briner, R.B. (Eds.). (2020). CEBMa Guideline for Rapid Reviews in Management and Organizations, Version 2.0. Center for Evidence Based Management, Amsterdam. www.cebma.org/guidelines/

Berg, F., Kölbel, J. F., & Rigobon, R. (2022). Aggregate Confusion: The Divergence of ESG Ratings*. Review of Finance, 26(6), 1315–1344. https://doi.org/10.1093/rof/rfac033

DOI: 10.34659/eis.2025.95.4.1170

Burnaev, E., Mironov, E., Shpilman, A., Mironenko, M., & Katalevsky, D. (2023). Practical AI Cases for Solving ESG Challenges. Sustainability, 15(17), Article 17. https://doi.org/10.3390/su151712731

Campbell, C., Sands, S., Ferraro, C., Tsao, H.-Y. (Jody), & Mavrommatis, A. (2020). From data to action: How marketers can leverage AI. Business Horizons, 63(2), 227–243. https://doi.org/10.1016/j.bushor.2019.12.002

Cavusgil, S. T., & Deligonul, S. Z. (2025). Dynamic capabilities framework and its transformative contributions. Journal of International Business Studies, 56(1), 33–42. https://doi.org/10.1057/s41267-024-00758-8

Chen, J., Wang, N., Lin, T., Liu, B., & Hu, J. (2024). Shock or empowerment? Artificial intelligence technology and corporate ESG performance. Economic Analysis and Policy, 83, 1080–1096. https://doi.org/10.1016/j.eap.2024.08.004

Chen, P., Chu, Z., & Zhao, M. (2024). The Road to corporate sustainability: The importance of artificial intelligence. Technology in Society, 76, 102440. https://doi.org/10.1016/j.techsoc.2023.102440

Chen, R., & Zhang, T. (2024). Artificial intelligence applications implication for ESG performance: Can digital transformation of enterprises promote sustainable development? Chinese Management Studies. Scopus. https://doi.org/10.1108/CMS-11-2023-0653

Chen, X., & Ge, L. (2025). Artificial intelligence and corporate ESG performance: Evidence from China. Applied Economics Letters, 0(0), 1–7. https://doi.org/10.1080/13504851.2025.2460713

Chen, Z., & Xie, G. (2022). ESG disclosure and financial performance: Moderating role of ESG investors. International Review of Financial Analysis, 83, 102291. https://doi.org/10.1016/j.irfa.2022.102291

Cheng, B., Ioannou, I., & Serafeim, G. (2014). Corporate social responsibility and access to finance. Strategic Management Journal, 35(1), 1–23. https://doi.org/10.1002/smj.2131

Chishti, M. Z., Xia, X., & Dogan, E. (2024). Understanding the effects of artificial intelligence on energy transition: The moderating role of Paris Agreement. Energy Economics, 131, 107388. https://doi.org/10.1016/j.eneco.2024.107388

Chollet, P., & Sandwidi, B. W. (2018). CSR engagement and financial risk: A virtuous circle? International evidence. Global Finance Journal, 38, 65–81. https://doi.org/10.1016/j.gfj.2018.03.004

Christensen, D. M., Serafeim, G., & Sikochi, A. (Siko). (2021). Why is Corporate Virtue in the Eye of the Beholder? The Case of ESG Ratings (SSRN Scholarly Paper 3793804). https://papers.ssrn.com/abstract=3793804

Chu, Z., Chen, P., Zhang, Z., & Chen, Z. (2024). Other's shoes also fit well: AI technologies contribute to China's blue skies as well as carbon reduction. Journal of Environmental Management, 353, 120171. https://doi.org/10.1016/j.jenvman.2024.120171

Clément, A., Robinot, É., & Trespeuch, L. (2022). Improving ESG Scores with Sustainability Concepts. Sustainability, 14(20), Article 20. https://doi.org/10.3390/su142013154

Cockburn, I. M., Henderson, R., & Stern, S. (2018). The Impact of Artificial Intelligence on Innovation (Working Paper 24449). National Bureau of Economic Research. https://doi.org/10.3386/w24449

Davenport, T. H., & Ronanki, R. (2018). Artificial intelligence for the real world. Harvard Business Review, 96(1), 108–116.

de Freitas Netto, S. V., Sobral, M. F. F., Ribeiro, A. R. B., & Soares, G. R. da L. (2020). Concepts and forms of greenwashing: A systematic review. Environmental Sciences Europe, 32(1), Article 1. https://doi.org/10.1186/s12302-020-0300-3

Department of International Cooperation Ministry of Science and Technology, P.R. China. (2017). *China's New Generation Artificial Intelligence Development Plan.* http://fi.china-embassy.gov.cn/eng/kxjs/201710/P020210628714286134479.pdf

Du, S., & Xie, C. (2021). Paradoxes of artificial intelligence in consumer markets: Ethical challenges and opportunities. Journal of Business Research, 129, 961–974. https://doi.org/10.1016/j.jbusres.2020.08.024

Escrig-Olmedo, E., Fernández-Izquierdo, M. Á., Ferrero-Ferrero, I., Rivera-Lirio, J. M., & Muñoz-Torres, M. J. (2019). Rating the Raters: Evaluating how ESG Rating Agencies Integrate Sustainability Principles. Sustainability, 11(3), Article 3. https://doi.org/10.3390/su11030915

European Commission. (2020). Taxonomy: Final report of the Technical Expert Group on Sustainable Finance. March 2020. https://finance.ec.europa.eu/system/files/2020-03/200309-sustainable-finance-teg-final-report-taxonomy_en.pdf

European Parliament and Council. (2022). Directive (EU) 2022/2464 of the European Parliament and of the Council of 14 December 2022 amending Regulation (EU) No 537/2014, Directive 2004/109/EC, Directive 2006/43/EC and Directive 2013/34/EU, as regards corporate sustainability reporting (Text with EEA relevance). https://eur-lex.europa.eu/eli/dir/2022/2464/oj/eng

European Parliament and Council. (2024). Regulation (EU) 2024/1689 of the European Parliament and of the Council of 13 June 2024 laying down harmonised rules on artificial intelligence and amending certain Union legislative acts (Artificial Intelligence Act). Official Journal of the European Union. https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX%3A32024R1689

Evans, G. L. (2017). Disruptive technology and the board: The tip of the iceberg. Economics and Business Review, 3(1), Article 1. https://doi.org/10.18559/ebr.2017.1.11

Federal Trade Commission. (2012). Guides for the Use of Environmental Marketing Claims. https://www.ftc.gov/sites/default/files/documents/federal_register_notices/guides-use-environmental-marketing-claims-green-guides/greenguidesfrn.pdf

Furman, J., & Seamans, R. (2019). AI and the Economy. Innovation Policy and the Economy, 19, 161–191. https://doi.org/10.1086/699936

Garritty, C., Hamel, C., Trivella, M., Gartlehner, G., Nussbaumer-Streit, B., Devane, D., Kamel, C., Griebler, U., & King, V. J. (2024). Updated recommendations for the Cochrane rapid review methods guidance for rapid reviews of effectiveness. BMJ, 384, e076335. https://doi.org/10.1136/bmj-2023-076335

Gillan, S. L., Koch, A., & Starks, L. T. (2021). Firms and social responsibility: A review of ESG and CSR research in corporate finance. Journal of Corporate Finance, 66, 101889. https://doi.org/10.1016/j.jcorpfin.2021.101889

Grant, M. J., & Booth, A. (2009). A typology of reviews: An analysis of 14 review types and associated methodologies. Health Information & Libraries Journal, 26(2), 91–108. https://doi.org/10.1111/j.1471-1842.2009.00848.x

Hamel, C., Michaud, A., Thuku, M., Affengruber, L., Skidmore, B., Nussbaumer-Streit, B., Stevens, A., & Garritty, C. (2020). Few evaluative studies exist examining rapid review methodology across stages of conduct: A systematic scoping review. Journal of Clinical Epidemiology, 126, 131–140. https://doi.org/10.1016/j.jclinepi.2020.06.027

Harker, J., & Kleijnen, J. (2012). What is a rapid review? A methodological exploration of rapid reviews in Health Technology Assessments. International Journal of Evidence-Based Healthcare, 10(4), 397–410. https://doi.org/10.1111/j.1744-1609.2012.00290.x

He, X. (2024). Can ESG performance drive firm innovation? The mediating role of AI adoption and digital transformation – evidence from China. International Journal of Innovation Management, 28(05N06). https://doi.org/10.1142/S1363919624500191

Holmström, J. (2022). From AI to digital transformation: The AI readiness framework. Business Horizons, 65(3), 329–339. https://doi.org/10.1016/j.bushor.2021.03.006

Huang, Y., Liu, S., Gan, J., Liu, B., & Wu, Y. (2024). How does the construction of new generation of national AI innovative development pilot zones drive enterprise ESG development? Empirical evidence from China. Energy Economics, 140. https://doi.org/10.1016/j.eneco.2024.108011

Hurwitz, J., Kaufman, M., & Bowles, A. (2012). Cognitive Computing and Big Data Analytics (1st ed.). John Wiley & Sons, Ltd. https://doi.org/10.1002/9781119183648

Iansiti, M., & Lakhani, K. (2020). Competing in the Age of AI: Strategy and Leadership When Algorithms and Networks Run the World, Harvard Business Review Press, Boston, MA.

Jahangirian, M., Eldabi, T., Garg, L., Jun, G. T., Naseer, A., Patel, B., Stergioulas, L., & Young, T. (2011). A rapid review method for extremely large corpora of literature: Applications to the domains of modelling, simulation, and management. International Journal of Information Management, 31(3), 234–243. https://doi.org/10.1016/j.ijinfomgt.2010.07.004

Jing, H., & Zhang, S. (2024). The Impact of Artificial Intelligence on ESG Performance of Manufacturing Firms: The Mediating Role of Ambidextrous Green Innovation. Systems, 12(11). https://doi.org/10.3390/systems12110499

Kar, A. K., Choudhary, S. K., & Singh, V. K. (2022). How can artificial intelligence impact sustainability: A systematic literature review. Journal of Cleaner Production, 376, 134120. https://doi.org/10.1016/j.jclepro.2022.134120

Karwowski, M., & Raulinajtys-Grzybek, M. (2021). The application of corporate social responsibility (CSR) actions for mitigation of environmental, social, corporate governance (ESG) and reputational risk in integrated reports. Corporate Social Responsibility and Environmental Management, 28(4), 1270–1284. https://doi.org/10.1002/csr.2137

Khangura, S., Konnyu, K., Cushman, R., Grimshaw, J., & Moher, D. (2012). Evidence summaries: The evolution of a rapid review approach. Systematic Reviews, 1(1), 10. https://doi.org/10.1186/2046-4053-1-10

Kotsantonis, S., & Serafeim, G. (2019). Four Things No One Will Tell You About ESG Data. Journal of Applied Corporate Finance, 31(2), 50–58. https://doi.org/10.1111/jacf.12346

Kuntz, T. (2023). ESG and the Weakening Business Judgment Rule (SSRN Scholarly Paper 4395003). Social Science Research Network. https://doi.org/10.2139/ssrn.4395003

Kuzey, C., Uyar, A., & Delen, D. (2014). The impact of multinationality on firm value: A comparative analysis of machine learning techniques. Decision Support Systems, 59, 127–142. https://doi.org/10.1016/j.dss.2013.11.001

Lee, C.-C., & Yan, J. (2024). Will artificial intelligence make energy cleaner? Evidence of nonlinearity. Applied Energy, 363, 123081. https://doi.org/10.1016/j.apenergy.2024.123081

Leitner-Hanetseder, S., & Lehner, O. M. (2022). AI-powered information and Big Data: Current regulations and ways forward in IFRS reporting. Journal of Applied Accounting Research, 24(2), 282–298. https://doi.org/10.1108/JAAR-01-2022-0022

Li, D., Zhang, Z., & Gao, X. (2024). Does artificial intelligence deter greenwashing? Finance Research Letters, 67. https://doi.org/10.1016/j.frl.2024.105954

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

Li, S., Younas, M. W., Maqsood, U. S., & Zahid, R. A. (2024). Impact of AI adoption on ESG performance: Evidence from Chinese firms. Energy & Environment, 0958305X241269041. https://doi.org/10.1177/0958305X241269041

Liang, H., & Renneboog, L. (2021). Corporate Social Responsibility and Sustainable Finance: A Review of the Literature. Corporate Social Responsibility and Sustainable Finance. https://doi.org/10.1093/acrefore/9780190625979.013.592

Lin, B., & Xu, C. (2024). Enhancing energy-environmental performance through industrial intelligence: Insights from Chinese prefectural-level cities. Applied Energy, 365, 123245. https://doi.org/10.1016/j.apenergy.2024.123245

Lin, B., & Zhu, Y. (2024). Does AI elevate corporate ESG performance? A supply chain perspective. Business Strategy and the Environment, 34(1), 586–597. Scopus. https://doi.org/10.1002/bse.3999

Liu, J., Chang, H., Forrest, J. Y.-L., & Yang, B. (2020). Influence of artificial intelligence on technological innovation: Evidence from the panel data of China's manufacturing sectors. Technological Forecasting and Social Change, 158(C). https://ideas.repec.org//a/eee/tefoso/v158y2020ics0040162520309689.html

Liu, X., Ma, C., & Ren, Y. (2024). How AI powers ESG performance in China's digital frontier? Finance Research Letters, 70. https://doi.org/10.1016/j.frl.2024.106324

Luqman, A., Zhang, Q., Talwar, S., Bhatia, M., & Dhir, A. (2024). Artificial intelligence and corporate carbon neutrality: A qualitative exploration. Business Strategy and the Environment, 33(5), 3986–4003. https://doi.org/10.1002/bse.3689

Matos, P. (2020). ESG and Responsible Institutional Investing Around the World: A Critical Review (SSRN Scholarly Paper 3668998). https://doi.org/10.2139/ssrn.3668998

Mori, M. (2023). AI as a Catalyst for ESG Investing. In Z. Hu, Z. Ye, & M. He (Eds.), Advances in Artificial Systems for Medicine and Education VI (pp. 15–24). Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-24468-1_2

Murè, P., Spallone, M., Mango, F., Marzioni, S., & Bittucci, L. (2021). ESG and reputation: The case of sanctioned Italian banks. Corporate Social Responsibility and Environmental Management, 28(1), 265–277. https://doi.org/10.1002/csr.2047

Nishant, R., Kennedy, M., & Corbett, J. (2020). Artificial intelligence for sustainability: Challenges, opportunities, and a research agenda. International Journal of Information Management, 53, 102104. https://doi.org/10.1016/j.ijinfomgt.2020.102104

Porter, M. E., Serafeim, G., & Kramer, M. (2019, October 16). Where ESG fails. Institutional Investor.https://www.institutionalinvestor.com/article/2bswdin8nvg922puxdzwg/opinion/where-esg-fails

Russell, S., & Norvig, P. (1995). Artificial Intelligence: A Modern Approach, Prentice-Hall, Upper Saddle River, NJ.

Sætra, H. (2023). The AI ESG protocol: Evaluating and disclosing the environment, social, and governance implications of artificial intelligence capabilities, assets, and activities. Sustainable Development, 31(2), 1027–1037. https://doi.org/10.1002/sd.2438

Saxena, A., Singh, R., Gehlot, A., Akram, S. V., Twala, B., Singh, A., Montero, E. C., & Priyadarshi, N. (2023). Technologies Empowered Environmental, Social, and Governance (ESG): An Industry 4.0 Landscape. Sustainability, 15(1), Article 1. https://doi.org/10.3390/su15010309

Smela, B., Toumi, M., Świerk, K., Francois, C., Biernikiewicz, M., Clay, E., & Boyer, L. (2023). Rapid Literature Review: Definition and Methodology. Journal of Market Access & Health Policy, 11(1), Article 1. https://doi.org/10.1080/20016689.2023.2241234

State Council of the People's Republic of China. (2021). China to build around 20 AI pilot zones by 2023. http://english.www.gov.cn/statecouncil/ministries/202112/06/content_WS61ae0e58c6d09c94e48a1c59.html

Su, W., Yu, J., & Zhao, L. (2025). Can Sci-Tech Finance Policy Boost Corporate ESG Performance? Evidence from the Pilot Experiment of Promoting the Integration of Technology and Finance in China. Sustainability, 17(6), Article 6. https://doi.org/10.3390/su17062332

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

Tricco, A. C., Antony, J., Zarin, W., Strifler, L., Ghassemi, M., Ivory, J., Perrier, L., Hutton, B., Moher, D., & Straus, S. E. (2015). A scoping review of rapid review methods. BMC Medicine, 13(1), 224. https://doi.org/10.1186/s12916-015-0465-6

UN Global Compact. (2004). Who cares wins: Connecting financial markets to a changing world. https://www.unglobalcompact.org/docs/issues_doc/Financial_markets/who_cares_who_wins.pdf

United States National Science and Technology Council. (2016). *The National Artificial Intelligence Research and Development Strategic Plan*. Networking and Information Technology Research and Development Subcommittee. https://www.nitrd.gov/pubs/national_ai_rd_strategic_plan.pdf

Vinuesa, R., Azizpour, H., Leite, I., Balaam, M., Dignum, V., Domisch, S., & Fuso Nerini, F. (2020). The role of artificial intelligence in achieving the Sustainable Development Goals. Nature Communications, 11(1), 233. https://doi.org/10.1038/s41467-019-14108-y

Wang, J., Wen, Y., & Long, H. (2024). Evaluating the mechanism of AI contribution to decarbonization for sustainable manufacturing in China. Journal of Cleaner Production, 472. https://doi.org/10.1016/j.jclepro.2024.143505

Wang, Q., Zhang, F., Li, R., & Sun, J. (2024). Does artificial intelligence promote energy transition and curb carbon emissions? The role of trade openness. Journal of Cleaner Production, 447, 141298. https://doi.org/10.1016/j.jclepro.2024.141298

Wang, S., & Zhang, H. (2024). Promoting sustainable development goals through generative artificial intelligence in the digital supply chain: Insights from Chinese tourism SMEs. Sustainable Development. https://doi.org/10.1002/sd.3152

Winston, A. (n.d.). (2024). Was a Bad Year for Sustainability. Harvard Business Review. https://hbr.org/2024/12/2024-was-a-bad-year-for-sustainability

Wohlin, C. (2014). Guidelines for snowballing in systematic literature studies and a replication in software engineering. Proceedings of the 18th International Conference on Evaluation and Assessment in Software Engineering, 1–10. https://doi.org/10.1145/2601248.2601268

Xiao, Y., & Xiao, L. (2025). The impact of artificial intelligence-driven ESG performance on sustainable development of central state-owned enterprises listed companies. Scientific Reports, 15(1), 8548. https://doi.org/10.1038/s41598-025-93694-y

Xie, H., & Wu, F. (2025). Artificial Intelligence Technology and Corporate ESG Performance: Empirical Evidence from Chinese-Listed Firms. Sustainability, 17(2), Article 2. https://doi.org/10.3390/su17020420

Zeng, F., Guo, Y., Fan, Q., & Wang, C. L. (2024). AI-orientation and company climate action: The moderating role of dependency structure and innovation capability. Industrial Marketing Management, 117, 148–160. https://doi.org/10.1016/j.indmarman.2023.12.018

Zhang, C. (2025). The Role of Big Data in Unveiling Greenwashing: A Study on its Impact on Corporate ESG Performance (SSRN Scholarly Paper 5098276). Social Science Research Network. https://doi.org/10.2139/ssrn.5098276

Zhang, C., & Shi, Y. (2024). ESG performance, product market competition, and high-quality corporate development. *Proceedings of the 2024 International Conference on Artificial Intelligence and Digital Management (ICAIDM 2024)*, 399–405. https://doi.org/10.2991/978-94-6463-578-2_56

Zhang, C., & Yang, J. (2024). Artificial intelligence and corporate ESG performance. International Review of Economics & Finance, 96. https://doi.org/10.1016/j.iref.2024.103713

Zhang, D. (2024). The pathway to curb greenwashing in sustainable growth: The role of artificial intelligence. Energy Economics, 133. https://doi.org/10.1016/j.eneco.2024.107562

Zhou, X., Li, G., Wang, Q., Li, Y., & Zhou, D. (2025). Artificial intelligence, corporate information governance and ESG performance: Quasi-experimental evidence from China. International Review of Financial Analysis, 102, 104087. https://doi.org/10.1016/j.irfa.2025.104087

Karolina ŁUDZIŃSKA

ZWIĄZEK MIĘDZY SZTUCZNĄ INTELIGENCJĄ A WYNIKAMI ESG NA POZIOMIE PRZEDSIĘBIORSTWA: SZYBKI PRZEGLĄD LITERATURY I AGENDA PRZYSZŁYCH BADAŃ

STRESZCZENIE: Niniejsze badanie eksploracyjne analizuje zależność między sztuczną inteligencją (AI) a wynikami przedsiębiorstw w zakresie ESG. Uwzględnia zarówno pozytywne efekty, jak i potencjalne ograniczenia wdrażania AI dla osiągania wyników ESG na poziomie firmy, identyfikując kluczowe zmienne moderujące z perspektywy koncepcji Zdolności Dynamicznych (Dynamic Capabilities Framework, DCF). Przeprowadzono szybki przegląd literatury (Rapid Literature Review, RLR), uzupełniony o wyszukiwanie metodą kuli śnieżnej, koncentrujące się na publikacjach w czasopismach Q1 i Q2. Wyniki wskazują na przeważająco pozytywną zależność między AI a wynikami ESG przedsiębiorstw. Mechanizmy, za pośrednictwem których AI przyczynia się do realizacji wyników ESG, koncentrują się wokół trzech powiązanych ze sobą obszarów: zdolności i cech organizacyjnych, technologicznych i operacyjnych mediatorów oraz czynników regionalnych i kontekstowych. Kluczowe korzyści wynikające z zastosowania AI obejmują usprawnienie przetwarzania danych i zarządzania informacją, wspieranie innowacyjności, ograniczanie zjawiska greenwashingu, ułatwianie transformacji cyfrowej, poprawę efektywności operacyjnej ESG oraz wzmocnienie mechanizmów kontroli wewnętrznej. Jednak skuteczność AI w poprawie wyników ESG pozostaje silnie zależna od kontekstu. Badanie to wnosi wkład w rozwijającą się debatę na temat transformacji ESG wspieranej przez AI, oferując uporządkowaną syntezę istniejących badań oraz wskazując na ich przyszłe kierunki.

SŁOWA KLUCZOWE: sztuczna inteligencja, AI, ESG, wyniki ESG, RLR

Appendix 1

Table A1. Concise Quality Appraisal Matrix for Studies Included in the Rapid Literature Review

No	Study (Year)	AI operationalization	ESG operationalization	Research design	Research Method	Endogeneity / Heterogeneity Controls
1	Chen et al. (2024)	AI indicators through precise vocabulary of the textual content of annual reports	ESG ratings from the CSI database	Unbalanced panel data from Chinese listed firms from 2007 to 2022, Cathay Pacific database (CSMAR)	Econometric model: Covariance and correlation tests, regression analysis	Endogeneity control: two-stage least squares regression, heterogeneity analysis (moderator: policy uncertainty)
2	Chen & Zhang (2024)	AI adoption at the firm level as an aggregated indicator	Sino-Securities Index ESG Ratings	Panel data from Chinese A-share listed companies from 2012 to 2022	Econometric model: Multivariate regression analysis	Firm and time fixed effects; heterogeneity analysis by technological intensity (high-tech vs. non-high-tech firms)
3	He (2024)	CSMAR database for AI adoption	Huazheng ESG Index (CSMAR database)	Panel data from Chinese A-share listed companies (Shanghai and Shenzhen) from 2010 to 2021	Econometric model: Regression analysis	Endogeneity control: natural logarithm of granted invention patents; industry heterogeneity analysis for manufacturing sector
4	Huang et al. (2024)	Exposure to the 2019 AIPZ policy in China as a quasi-natural experiment	CSI ESG Index	Unbalanced panel data of Chinese Shanghai and Shenzhen listed companies from 2007 to 2022	Multi-period difference-in-differences (DID) model; PSM-DID method	Endogeneity control: implied DID; specific tests not reported
5	Jing & Zhang (2024)	AI dictionary of 73 keywords related to AI	Huazheng ESG ratings and scores in the Wind database	Panel data from A-share manufacturing companies listed on the Shanghai and Shenzhen stock exchanges from 2012 to 2022	Regression and correlation analysis	Endogeneity controls: instrumental variable (IV) method, propensity score matching, placebo test; heterogeneity analysis: ambidextrous green innovation balancing, enterprise size
6	Li et al. (2024)	AI-related words in corporate annual reports as a proxy for AI	Greenwashing vs. ESG Performance (Own Model)	Panel data from A-share public firms in China from 2012 to 2022	Econometric model: Regression analysis	Endogeneity control: two-step GMM estimation; heterogeneity analysis: political affiliation, female directors, equity incentives
7	Lin & Zhu (2024)	Exposure to the 2019 AIP policy in China as a quasi-natural experiment	Zhongzheng ESG scores as the metric for gauging corporate ESG performance	Multi-period difference-in-differences (DID) model	Econometric model: Regression analysis	Endogeneity control: parallel trend test, placebo test
8	Liu et al. (2024)	Level of AI development of the firm as a proxy	Firm's ESG scores as proxies for ESG performance	Panel data from Chinese A-share listed firms, 2009–2022	Econometric model: Regression analysis	Endogeneity control: tests for multicollinearity and alternative dependent variables; heterogeneity analysis by industry type, ownership (SOEs vs. non-SOEs), and regional digital inclusion
9	Sætra (2023)	Theoretical protocol/tool	n/a	Theoretical	Theoretical discussion	n/a
10	Wang et al. (2024)	AI-related words in corporate annual reports as a proxy for measuring the degree of intelligent manufacturing	ESG performance proxy: carbon data for public manufacturing companies (2004–2020) from the Carbon Neutral Database Instructions (CSMAR)	Panel data from 2,607 manufacturing firms listed in Chinese stock markets, 2004–2020	Econometric regression models, mediation analysis	Heterogeneity tests: industrial and spatial heterogeneity of AI effects on carbon intensity

DOI: 10.34659/eis.2025.95.4.1170

No	Study (Year)	AI operationalization	ESG operationalization	Research design	Research Method	Endogeneity / Heterogeneity Controls
11	Wang & Zhang (2024)	Generative AI performance through three steps	ESG performance through three steps	Two-phase longitudinal survey of 429 tourism SMEs in China	Two-phase longitudinal survey model examining generative AI, digital supply chain innovation, supply chain collaboration, customer involvement, and ESG performance	Endogeneity control: two-phase tracking survey method to avoid common method bias; single-factor analysis, marker variable techniques, variance inflation factor thresholds, independent samples t-test
12	Zhang & Yang (2024)	AI adoption index based on a novel text-based measure capturing the extent of AI integration in firms' operations using ML processing techniques on Management Discussion and Analysis (MD&A) sections of corporate annual reports	ESG composite score (E, S, and G factors) derived from the Sino-Securities ESG database	Panel data of 26,509 firm-year observations of Chinese firms from 2010 to 2022	Econometric models: baseline regression, two-way fixed effects, Heckman two-stage estimation, Tobit model	Endogeneity tests: instrumental variable (IV) approach, propensity score matching (PSM), heterogeneity analysis by organizational life-cycle stage and industry characteristics
13	Zhang (2024)	AI status calculated by the ratio of per capita artificial intelligence patents	Greenwashing vs. ESG (difference between firm-level standardized ESG rating and disclosure scores)	Panel data from Chinese listed firms (China Stock Market & Accounting Research Database), 2014–2021	Econometric model: Regression analysis	Endogeneity control: robustness tests with alternative ESG measures; heterogeneity analysis by ownership and industry; institutional development controls
14	Chen & Ge (2025)	Natural logarithm of the frequency of AI-related keywords plus one, based on annual reports	Huazheng ESG composite scores	Panel data from A-share listed enterprises on the Shanghai and Shenzhen Stock Exchanges, 2009–2022	Econometric model: Regression analysis	Endogeneity control: exogenous shock analysis
15	Li et al. (2025)	Natural logarithm of AI-related patent counts (primary measure); AI-related keyword frequency in corporate disclosures (alternative measure for robustness tests)	CNRDS ESG ratings (primary measure); Sino-Securities ESG scores (alternative measure for robustness)	Panel data from Chinese A-share listed companies, 2011–2022	Econometric models: baseline, mediation, moderation, multicollinearity analysis	Endogeneity analysis: lagged AI capabilities as an instrument; PSM; Heckman two-stage model; heterogeneity by firm size, leverage, board structure, industry type, and ownership
16	Li et al. (2024)	AI adoption manually collected from Management Discussion and Analysis (MD&A) sections of annual reports available on CNINFO	ESG disclosure information from the Shanghai Huazheng Information Service	Panel data from Chinese A-share listed companies on the Shanghai and Shenzhen stock exchanges, 2009–2021	Econometric model: Regression analysis; correlation matrix	Endogeneity analysis: propensity score matching (PSM), alternative variable analysis, omitted variable bias test; heterogeneity analysis: low vs. high fintech industries
17	Saxena et al. (2023)	Theoretical (Industry 4.0 / AI for ESG data)	n/a	Theoretical	Conceptual framework	n/a
18	Xiao & Xiao (2025)	AI proxy based on text analysis of the frequency of AI-related terms in annual reports of publicly listed companies	Huazheng ESG Index	Panel data from publicly listed central state-owned enterprises in China, 2016–2022	Mixed-methods approach: regression models, mediation models, in-depth interviews, document analysis	Endogeneity control: two-way fixed effects for industry and year

DOI: 10.34659/eis.2025.95.4.1170

No	Study (Year)	AI operationalization	ESG operationalization	Research design	Research Method	Endogeneity / Heterogeneity Controls
19	Xie & Wu (2025)	Degree of AI technology adoption measured as the ratio of the book value of robots to the number of employees (within logarithmic processing)	ESG scores from the CNRDS database	Panel data of 4,858 listed corporations in China, 2007–2022	Econometric model: Regression analysis	Endogeneity tests: sample self-selection, omitted variables, reverse causality; heterogeneity tests by industry competition, firm intensity, and regional variation
20	Zhou et al. (2025)	Dummy variable for the AIPZ policy based on 697 publicly listed firms in 18 cities designated as AI pilot zones	Huazheng ESG composite scores	Panel data from China's national AI pilot zones as a quasi-natural experiment; staggered difference-in-differences (DID) approach using panel data from 1,418 A-share listed firms (2011–2022)	Staggered DID approach to assess the impact of AIPZ policy on ESG performance	Endogeneity controls: parallel trend test, placebo test; heterogeneity analysis across groups and over time; Bacon decomposition to check DID validity

DOI: 10.34659/eis.2025.95.4.1170