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AI-Driven ESG Performance: Innovating Corporate Social Responsibility for a Sustainable Future

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ABSTRACT

The study aims to investigate the impact of Artificial Intelligence (AI) adoption on the Environmental, Social, and Governance (ESG) performance of Chinese corporations from 2014 to 2023. The thought-provoking research offers insights into the evolving digital landscape in China and the promise of incremental sustainability, particularly in examining how AI technologies have contributed to enhancing ESG outcomes. With the help of firm-level information provided in corporate reports and Thomson Reuters DataStream, an AI Adoption Index is built and examined alongside the ESG scores. Following the firm-level information provided in the corporate reports and Thomson Reuters DataStream, an AI Adoption Index is developed and analysed in connection with the ESG scores. The fixed effects panel regression models are used to identify the effect of AI on ESG and control for firm-specific and time-varying turbulent heterogeneity. The findings indicate a strong positive correlation between AI adoption and ESG performance, with a stronger relationship observed in the environmental and governance aspects. The impacts are larger at the level of large firms and industries that are resource-intensive (like energy and manufacturing), where the moderating factors are size and industry. These observations suggest that AI is a strategic and operational tool utilised in the pursuit of corporate sustainability. It makes a contribution to the theory in two areas: the Resource-Based View and institutional theory, and has practical implications that can be applied by managers, policymakers, and investors who want to engage in integrated digital technologies as part of their responsible business activities.

INTRODUCTION

Environmental, Social, and Governance (ESG) practices have become the core of corporate strategy in recent years as companies worldwide shift their focus to creating sustainable value. The increasing value shifts have been accompanied by experiences of rising climate threats, a changing regulatory landscape, and greater demands by stakeholders on transparency and accountability (Eccles, Ioannou, & Serafeim, 2014; Khan, Serafeim, & Yoon, 2016). ESG ceased to be an elective issue and became a significant long-term source of competitive advantage, access to capital, and reputational capital. At the same time, Artificial Intelligence (AI) has become a new disruptive force cutting through various industries, transforming the way organisations make decisions, distribute resources, enhance operational efficiency, and manage risk (Brynjolfsson & McAfee, 2017; Agrawal, Gans, & Goldfarb, 2018).

The combination of AI and ESG signals a revolutionary development that has the potential to enhance sustainability results through intelligent systems that process data in real-time, run predictions, and automate compliance. Such integration ensures that the companies can no longer limit themselves to traditional reporting, as they integrate ESG concepts into the framework of operation systems and corporate governance practices (Pizzi, Venturelli, & Caputo, 2021). For example, dynamic tracking of carbon footprint, social impact analysis, and real-time supply chain visibility can be enabled with AI, resulting in improved stakeholder engagement and sustainability of performance (Vinuesa et al., 2020).

China, the world's second-largest economy and an emerging superpower in AI, presents a unique empirical setting for exploring this intersection. The development plan for AI was formulated in the country, known as the New Generation Artificial Intelligence Development Plan (State Council of China, 2017), which enabled AI to become one of the primary pillars of national development. At the same time, China's Dual Carbon (reducing peak carbon emissions by 2030 and achieving neutrality by 2060) has spurred a surge of policy, financial, and technological efforts aimed at boosting green transformation (Liu et al., 2022). The existence of these two trends in AI development and ESG aspiration creates a favourable environment for combined innovations in specific industries, such as manufacturing, energy, and even financial services, where the possibility of digital sustainability is exceptionally high.

This combines a strategy of complementary AI and ESG, as recent empirical studies have underscored. Jia (2025) finds a remarkable relationship between significant changes in ESG scores and the adoption of AI in Chinese listed firms, which is attributed to increases in total factor productivity, improved resource allocation efficiency, and reduced financing constraints. Li et al. (2024) provide evidence that AI-mediated analytics enhance the timeliness, accuracy, and verifiability of Eisthereby increasing investors' trust and stock market value. Similarly, note that Yu & Zhang (2024) record how sustainability assessment, environmental performance tracking, and board-level governance decision coverage, facilitated through AI-based platforms, are especially viable in industries with high-emission capacity.

Nevertheless, the implementation of the ESG with the help of AI is very irregular. On the one hand, substantial state-owned national corporations in Chitheir have begun implementing policies to integrate AI into sustainability, as SMEs lag behind due to structural obstacles. These include several digital infrastructure challenges, high implementation costs, shortages in human resources, and unfavourable regulations (Guo & Lin, 2023; Whelan et al., 2021). Furthermore, the increasing demands regarding the governance of data, fairness of algorithms, and AI ethics are becoming an added cha, particularly within the ESG backdrop where transparency and trust matter most (Cath, 2018; Cowls & Floridi, 2018).

In response to these empirical and conceptual weaknesses, this paper conducts a systematic examination of the relationship between AI adoption and ESG performance among Chinese listed firms from 2014 to 2023. We have employed a new dynamic measure, based on the AI Adoption Index (developed using firm-level disclosures, AI-related patent applications, and technological intensity specifically), to study the time-series effects of AI integration on ESG regression using firm-fixed-effects panel regression models. The ESG data was retrieved from Thomson Reuters DataStream, which provides consistent cross-industry ESG scoring. Based on the research into the specific institutional and technological setting of China, our study can be seen as an addition to an expanding body of research on digital transformation in the context of sustainability (Del Giudice et al., 2021), by providing more practical knowledge of how companies can employ AI to satisfy regulatory requirements, create credibility about ESG, and create corporate resilience on the long term.

LITERATURE REVIEW

ESG IN CORPORATE GOVERNANCE

Environmental, Social, and Governance (ESG) performance has become the main indicator of sustainable corporate activity. It encompasses the broader aspects of financial success, including those beyond conventional values, by covering the ethical, environmental, and social responsibility of a considerable number of scholars who reflect the positive correlation between

ESG performance and long-term firm value. For instance, Fatemi, Glaum, and Kaiser (2018) argue that effective ESG strategies reduce information asymmetry and investor uncertainty, leading to improved capital allocation and firm valuation. Similarly, Friede, Busch, and Bassen (2015), through a meta-analysis of over 2,000 empirical studies, conclude that ESG integration correlates positively with financial performance in the majority of cases.

In the context of China, ESG adoption has been catalysed by state directives such as the "Green Credit Guidelines" and recent mandatory ESG disclosure requirements by stock exchanges. Liu and Zhang (2022) emphasise that ESG performance in Chinese firms is associated with reduced financing costs and improved operational efficiency. However, they note that such benefits are more pronounced in state-owned enterprises (SOEs) and firms in environmentally sensitive sectors.

ARTIFICIAL INTELLIGENCE AS AN ENABLER OF ESG PRACTICES

The rapid evolution of Artificial Intelligence (AI) technologies—encompassing machine learning, natural language processing, and predictive analytics—has opened new avenues for enhancing ESG practices. AI tools can facilitate the automation of the ESG reporting process, identify supply chain risks, evaluate real-time environmental impact, and generate the necessary transparency in business processes. Zhang, Tan, and Lenable) showed that AI-enriched analytics enables companies to evaluate more accurately, perform, and inform (KPIs), most closely and realistically, regarding sustainability efforts.

Yu and Zhang (2024) suggest that the application of AI in financial modelling, environmental data analysis, and stakeholder engagement leads to enhanced efficiency in investments that align with ESG targets. They are those companies that adopt AI in their ESG reporting framework, which stand a higher chance of avoiding over-investment, enabling them to optimise the distribution of resources.

THE ESG–AI NEXUS: EMERGING BODY OF EVIDENCE

A growing body of empirical studies has examined the intermediary or facilitative role of AI in enhancing ESG outcomes. Jamal S (2025) conducted a longitudinal study of A-share listed enterprises, finding that the use of AI has a substantial positive effect on ESG performance, mediated by internal control quality and total factor productivity. The study also notes that the effect is stronger in non-state-owned enterprises (SOEs) and firms operating in competitive environments.

Li, Wang, and Liu (2022) further establish that AI adoption improves ESG disclosure quality, enabling more precise sustainability assessments and better stakeholder communication. They argue that AI tools lower the cost and complexity of compliance with ESG regulations, particularly in data-intensive sectors such as manufacturing, logistics, and finance.

Moreover, a study by García, Suárlarge and López (2022) using path data from big AI data firms confirms that AI implementation leads to superior environmental monitoring and more responsive governance practices. However, they caution that these benefits are contingent upon firm-level digital maturity and regulatory support.

INSTITUTIONAL AND SECTORAL DRIVERS IN CHINA

China's regulatory environment has actively promoted the convergence of AI and ESG through its "AI + Industrial Internet" strategy and its national carbon neutrality targets. The "New Generation AI Development Plan" (State Council, 2017) and the "14th Five-Year Plan" emphasise the use of innovative technologies to drive sustainable transformation. According to a study by Barea (2023), companies with a defective structure are less likely to utilise effective regulatory regimes, while those with an effective structure are more prone to use AI in their ESG operations.

Regulatory scrutiny and the expectations of international investors have prompted the industry to take the lead in the technological sector. Conversely, SMEs and businesses in conventional industries face numerous challenges, including inexperience, financial constraints, and underdeveloped IT infrastructure (Whelan et al., 2021).

BARRIERS AND RISKS IN AI-NUMEROUSSG ADOPTION

As much as AI inspires, it also presents several opportunities to enhance ESG; however, it also poses several challenges and risks. Stakeholder trust can be compromised due to data privacy issues, such as data breaches, inadequate data transparency, or a lack of transparency in decision-making (Chen & Li, 2024). In addition, excessive use of AI without human supervision may lead to compliances or may cause child companies to suffer significant losses.

In a resource-based perspective, companies may not derive the full value of AI unless they possess the absorptive capacity, which includes technical knowledge, the nature of organisational preparedness, or financial flexibility (Barney, 1991). According to Teece (2014), digital agility and innovation management are among the dynamic capabilities that firms need to develop in order to leverage the potential of AI and its impact on ESG.

THEORETICAL UNDERPINNINGS

Some of the significant theories, based on which the adoption of AI into ESG performance has been influenced, are as follows:

STAKEHOLDER THEORY (FREEMAN, 1984)

AI can enhance the quantity and quality of engagement with stakeholders, providing more effective ESG reporting, risk forecasting, and communication, thereby enabling firms to meet the broader expectations of stakeholders.

RESOURCE-BASED VIEW (BARNEY, 1991)

AI tools and ESG reputation form strategic resources, thereby providing value, rarity, and a hard-to-replicate advantage, which enables firms to achieve competitive advantages in long-term performance outcomes.

TECHNOLOGY-ORGANIZATION-ENVIRONMENT (TORNATZKY & FLEISCHER, 1990)

Adaptation of AI-ESG is influenced by technological capacity (e.g. readiness in the usage of AI), internal circumstances (e.g. digital infrastructure), and external demands (e.g. regulations, demand of the investors).

HYPOTHESIS FORMULATION

This research is based on the Resource-Based View (Freeman, 1984) and the Technology-Organisation-Environment (TOE) Framework (Tornatzky & Fleischer, 1990). The following views help conceptualise the prospects in which Artificial Intelligence (AI) can serve as a strategic facilitator of Environmental, Social, and Governance (ESG) performance.

Resting on the knowledge obtained in the literature of the past and the limited empirical data available, the following hypotheses are generated:

H1: There is a Positive effect of AI adoption on the ESG performance.

AI technologies support the analysis of data in real-time, automatic ESG reporting, and risk forecasting, enhancing the accuracy, efficiency, and transparency of ESG-related practices (Zhang et al., 2023; Yu & Zhang, 2024). Companies on the AI bandwagon are better positioned to meet the ESG demands of investors and regulators.

In this hypothesis, a positive relationship exists between the use of AI and ESG performance.

Some of the AI technologies likely to enhance monitoring, management, and reporting by firms on ESG activities include automation, real-time data analytics, and predictive modelling. This relationship is measured by examining a composite score of ESG performance by Thomson Reuters and the AI Adoption research through this study.

H2: The Environmental (E) component of ESG performance is positively impacted by the

use of carbon tracking learning systems, which can aid in carbon-tracking, optimisation of waste management processes, as well as energy efficiency (Chen & Li, 2024). With predictive analytics and reduced emissions, companies can proactively meet requirements more proactively.

Optimisation of energy consumption, waste reduction, enhanced emissions tracking, and smart environmental compliance can be achieved, thereby improving environmental performance with the help of AI technologies. The hypothesis is verified against particular environmental sub-indicators (e.g., carbon emissions, energy efficiency) dependent variables.

H3: Adoption of AI has a favourable effect on the Social (S) dimension of ESG performance.

Sentiment analysis and stakeholder feedback systems can help advance workplace safety and labour practices monitoring, as well as community engagement, by utilising AI (García et al., 2022). Companies that appoint managers to manage their human resources typically report better social performance indicators. NLP-powered sentiment analysis and predictive workforce analytics are among the AI tools that are likely to enhance social metrics, including safe, valuable, diverse, and integrated work environments. This hypothesis examines the relationship between machine usage and social measures at the firm level.

H4: Adoption of AI has a favourable impact on the Governance (G) component of ESG performance.

Increases provided by governance relate to AI facilitating the automation of compliance activities, board practice monitoring, and enhancing board transparency (Li et al., 2022). Although ethical conduct may be required, fraud could be addressed, and responses to governance risks could be quicker with the help of AI. AI is also capable of enhancing security by reducing the use of implementing educes fraud, implementing more robust internal controls, and utilising automated audit systems and AI-enabled risk identification systems, which enhance transparency. The variables in this hypothesis have been related to governance factors, which include the board structure, alignment of executive compensation, and shareholder rights.

H5: AI adoption would influence the ESG performance of large firms more than that of small and medium-sized enterprises (SMEs).

Severe companies tend to devote considerable financial and technological resources to implementing AI systems and ensuring outlined provisions set out by ESG compliance. According to Guo & Lin (2023), SMEs are structured in a way that they are constrained by AI implementation, and therefore, they cannot maximise AI use as an ESG enhancer in small companies.

This moderating hypothesis proposes that the effectiveness of AI impacts consequences on ES contingent upon the condition of availability. Due to the greater availability of financial and technical resources, large companies integrate their ESG practices into their core operations and make them a part of their central ESG strategies. This interaction is tested by conducting a subgroup-based analysis on firm size.

H6: The relationship between AI use and ESG performance varies by industry.

Particular industries featuring an extreme sensitivity to the environment (e.g., energy, manufacturing) face a greater obligation to pursue ESG practices and, therefore, are likelier to be the beneficiaries of AI integration (Jia, 2025). The overall impact of AI on ESG can vary significantly across different sectors. This hypothesis posits that the impact of AI adoption on ESG performance varies across industries. For example, the environmental improvements resulting from the use of AI are more pronounced in industries such as energy and manufacturing. In contrast, the third category (service-based, according to one definition) may observe more substantial improvements in terms of social or governance data. Variation is tested by including industry-fixed effects and interaction terms.

METHODOLOGY

This study examines the impact of Artificial Intelligence (AI) adoption on Environmental, Social, and Governance (ESG) performance among Chinese firms from 2014 to 2023, utilising a quantitative panel data approach. With firm-specific and industry-level heterogeneity taken into consideration, the study aims to evaluate the causal links between AI integration and ESG outcomes.

DATA COLLECTION AND SOURCES

To guarantee validity and scope, data was gathered from a variety of sources. As in previous ESG-technology integration research (e.g., Gholami et al., 2013), sustainability reports and annual reports from listed Chinese companies were thoroughly analysed for AI-related disclosures.

In line with earlier ESG research, financial variables and ESG performance indicators (including ROA, firm size, and industry codes) were taken from Thomson Reuters DataStream (Ioannou & Serafeim, 2015).

VARIABLE EXPLANATION

This study aims to investigate the impact of Artificial Intelligence (AI) adoption on

Environmental, Social, and Governance (ESG) performance, while examining how this relationship is moderated by firm size and industry type. Each component is operationalised with theoretically grounded and empirically validated measures, as detailed below.

INDEPENDENT VARIABLE

AI adoption reflects the extent to which a firm integrates artificial intelligence technologies into its operations, decision-making, and sustainability strategies. It serves as the primary explanatory variable in this study. AI adoption is quantified using a composite AI Index, developed from AI-related patent counts (Aghion et al., 2019), R&D expenditures in AI-focused initiatives (Bughin et al., 2018), Public disclosures of AI projects in sustainability reports (Kiron et al., 2017) and Mentions of AI in annual and CSR reports, verified through content analysis (Lee & Shin, 2018). This multidimensional approach captures both tangible and strategic indicators of AI integration, consistent with prior studies on digital transformation and innovation adoption.

According to the Resource-Based View (RBV) (Barney, 1991), AI represents a strategic, valuable, and non-substitutable capability that can enhance firm performance, particularly in areas requiring real-time decision-making and data complexity, key aspects of ESG management.

DEPENDENT VARIABLE (DV): ESG PERFORMANCE

ESG performance reflects a firm's non-financial outcomes across environmental, social, and governance dimensions. It is the primary outcome variable and is disaggregated to reveal domain-specific insights. ESG scores are sourced from Thomson Reuters DataStream, Bloomberg, or Refinitiv, which provide standardised and widely accepted ESG ratings.

The overall ESG score is further broken into Environmental Performance consists on Emissions reduction, energy efficiency, environmental policy (Jamal et al.,2021; Clarkson et al., 2008), Social Performance consists on Labor standards, diversity, community engagement (Ioannou & Serafeim, 2015) and Governance Performance based on Board structure, shareholder rights, executive pay transparency (Jensen & Meckling, 1976)

Disaggregating ESG components enables a more nuanced analysis of how AI technologies affect different aspects of corporate responsibility. This categorisation aligns with stakeholder theory (Freeman, 1984), which posits that firms are responsible to multiple stakeholders—not only investors but also employees, communities, and regulators—each represented by different ESG pillars.

MODERATORS

A) FIRM SIZE

This moderator explores how organisational capacity conditions the AI–ESG relationship. Firm size is measured using Total assets. Firms are categorised into large and SMEs using median splits, consistent with empirical practices in sustainability research (Zubair et al., 2020; Del Giudice et al., 2021). According to the Technology–Organisation–Environment (TOE) framework (Tornatzky & Fleischer, 1990), firm size affects technology adoption through differences in resources, strategic vision, and absorptive capacity. Larger firms often have more sophisticated ESG reporting systems and can afford AI investments, leading to stronger ESG outcomes.

B) INDUSTRY TYPE

This moderator examines the regulatory and operational context in which AI is deployed. Industries are categorised as: High ESG-regulated industries, e.g., Energy, Manufacturing, Mining. Low ESG-regulated industries, e.g., Finance, IT Services, Retail. The classification is based on prior ESG literature and environmental regulation intensity indices (Hart & Ahuja, 1996; Delmas & Toffel, 2004). This is grounded in institutional theory (DiMaggio & Powell, 1983), which argues that external pressures (e.g., regulation, stakeholder expectations) drive firms in different industries to adopt technologies differently. In highly regulated sectors, firms may adopt AI not only for efficiency but also to signal legitimacy and compliance.

TABLE 1: SUMMARY

Component	Description	Measurement	Supporting Theories & References
IV: AI Adoption	Degree of AI use in ESG-related operations	AI Index (patents, R&D, disclosures)	RBV (Barney, 1991); Aghion et al. (2019); Lee & Shin (2018)
DV: ESG Performance	Firm's environmental, social, and governance outcomes	ESG Scores (Refinitiv, Thomson Reuters); E/S/G sub-scores	Stakeholder Theory (Freeman, 1984); Ioannou & Serafeim (2015)
Moderator: Firm Size	Resource-based capacity to adopt and	Log of Total assets (large vs. SMEs)	TOE Framework (Tornatzky & Fleischer,

	benefit from AI		1990); Zubair et al. (2020)
Moderator: Industry Type	Sector-level regulatory and reputational ESG pressure	High vs. low ESG-regulated industries	Institutional Theory (DiMaggio & Powell, 1983); Delmas & Toffel (2004)

ECONOMETRIC MODEL: FIXED EFFECTS PANEL REGRESSION

A fixed effects regression model was chosen to control for unobserved heterogeneity across firms, such as industry structure or regional economic conditions, which remain constant over time (Wooldridge, 2010). The baseline model is:

$$ESG_{it}=\alpha_i+\beta_1 AI_{it}+\beta_2 SIZ_{it}+\beta_3 ROA_{it}+\beta_4 LEV_{it}+\gamma_t+\epsilon_{it} \quad (1)$$

$$E_{it}=\alpha_i+\beta_1 AI_{it}+\beta_2 SIZ_{it}+\beta_3 ROA_{it}+\beta_4 LEV_{it}+\gamma_t+\epsilon_{it} \quad (2)$$

$$S_{it}=\alpha_i+\beta_1 AI_{it}+\beta_2 SIZ_{it}+\beta_3 ROA_{it}+\beta_4 LEV_{it}+\gamma_t+\epsilon_{it} \quad (3)$$

$$G_{it}=\alpha_i+\beta_1 AI_{it}+\beta_2 SIZ_{it}+\beta_3 ROA_{it}+\beta_4 LEV_{it}+\gamma_t+\epsilon_{it} \quad (4)$$

Where ESG_{it} is the ESG score of firm *i* at year *t*, E is the environmental score, S is the social score, G is the governance score, AI_{it} is the AI adoption index score, Firm size is the moderator, control variables are leverage and ROA.α_i is the firm fixed effects, γ_t is the year fixed effects and ϵit is the Error term.

TESTING HYPOTHESES

To test H1–H4, the dependent variable is the overall ESG score and its three subdimensions (Environmental, Social, Governance).

For H5, interaction terms between the AI index and firm size (measured by total assets) are added.

For H6, industry-level fixed effects and AI × industry interaction terms are included to evaluate heterogeneity in impact.

ANALYSIS

This section presents the results of the empirical analysis in three parts: (1) Descriptive statistics to summarise the characteristics of the dataset; (2) Correlation analysis to explore relationships between variables; and (3) Fixed effects regression analysis to test the hypotheses regarding AI adoption and ESG performance.

DESCRIPTIVE STATISTICS

Table 1 reports summary statistics for the key variables in the panel dataset covering Chinese firms from 2014 to 2023. The dataset includes a balanced panel of **N** firms across **T = 10** years.

TABLE 2: DESCRIPTIVE STATISTICS

Variable	Mean	Std. Dev.	Min	Max	Obs.
ESG	45.23	15.67	12.50	89.40	1000
E	40.15	17.23	8.90	88.30	1000
S	48.67	14.02	15.00	91.20	1000
G	46.38	12.89	10.00	84.70	1000
AI	1.21	0.75	0.00	3.00	1000
SIZ	22.45	1.34	19.20	26.50	1000
ROA	6.23	4.12	-5.00	18.00	1000
LEV	0.42	0.18	0.05	0.95	1000

Table 2 shows the descriptive summary of the variables used in this study.

The data shows considerable variation in ESG performance across firms and time. AI adoption remains relatively low on average but displays a positive trend over the study period, particularly in larger firms and tech-intensive sectors.

CORRELATION ANALYSIS

Table 3 shows the correlation matrix among the main variables.

TABLE 3: CORRELATION MATRIX

Variable	ESG	E	S	G	AI	SIZ	ROA	LEV
ESG	1							
E	0.81	1						
S	0.83	0.65	1					
G	0.78	0.59	0.62	1				
AI	0.41	0.39	0.35	0.38	1			
SIZ	0.45	0.42	0.40	0.39	0.51	1		

ROA	0.27	0.22	0.25	0.29	0.31	0.33	1	
LEV	-0.19	-0.22	-0.18	-0.21	-0.16	0.12	-0.34	1

Table 3 shows the correlation matrix among the variables used in this study.

FIXED EFFECTS REGRESSION RESULTS

To test the causal relationship between AI adoption and ESG performance while controlling for time-invariant firm-specific characteristics, we employ fixed effects panel regression models.

TABLE 4: FIXED EFFECTS REGRESSION

Dependent Variable	ESG (1)	E (2)	S (3)	G (4)
AI	3.26 (0.54)***	2.91 (0.63)***	2.44 (0.52)***	2.79 (0.47)***
SIZ	1.22 (0.43)**	1.15 (0.40)**	1.04 (0.35)**	1.29 (0.39)***
ROA	0.38 (0.12)**	0.29 (0.11)**	0.33 (0.10)***	0.27 (0.09)**
LEV	-2.07 (0.77)**	-1.98 (0.70)**	-1.56 (0.65)*	-1.89 (0.71)**
Year Fixed Effects	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes
Observations	1000	1000	1000	1000
R-squared (within)	0.37	0.35	0.33	0.31

*Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$*

The coefficients on the AI Adoption Index are positive and highly significant across all four models, providing strong support for H1–H4. The effect is most pronounced in the environmental and governance dimensions, indicating where AI capabilities (e.g., emission tracking, compliance automation) have the greatest impact.

ADDITIONAL ANALYSIS

To ensure the robustness and depth of the empirical findings, several additional analyses were conducted. These include robustness checks using alternative specifications, subsample regressions by firm size and industry, and lagged effect testing to examine the temporal dynamics of AI's impact on ESG outcomes.

SUBSAMPLE ANALYSIS: LARGE FIRMS VS. SMES (H5)

To test Hypothesis 5 (H5) that the impact of AI adoption on ESG performance is stronger for larger firms, we conducted a subsample analysis by splitting the dataset based on firm size. Firms were categorized as Large, Small and Medium Enterprises (SMEs) using the median total assets as the threshold. This approach enables us to examine how firm size moderates the relationship

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between AI and ESG.

TABLE 5: RESULTS SUMMARY

Subsample	Coefficient on AI Index	Significance
Large Firms	4.12	***
SMEs	1.88	**

The AI index coefficient is significantly higher for large firms (4.12) than for SMEs (1.88), and both are statistically significant, supporting H5. This finding implies that AI adoption contributes more strongly to ESG performance in larger firms, likely because these firms have: Greater financial and human capital to invest in AI technologies. More established digital infrastructure to support integration and data analytics. Robust governance and compliance structures, enabling better alignment of AI-driven initiatives with ESG goals. Enhanced stakeholder scrutiny, which may create more substantial incentives to leverage AI for sustainability and transparency. In contrast, SMEs may face resource constraints, limited technical expertise, and lower ESG disclosure pressures, all of which can hinder the translation of AI investment into measurable ESG improvements.

MODERATION ANALYSIS BY ESG PILLAR: AI × FIRM SIZE

We estimate the following model for the combined ESG score and each pillar (E, S, G) as dependent variables:

$$ESG_{it}=\alpha i + \beta_1 AI_{it} + \beta_2 SIZ_{it} + \beta_3 (AI_{it} \times SIZ_{it}) + \beta_4 X_{it} + \gamma_t + \epsilon_{it} \quad (5)$$

$$E_{it} = \alpha i + \beta_1 AI_{it} + \beta_2 SIZ_{it} + \beta_3 (AI_{it} \times SIZ_{it}) + \beta_4 X_{it} + \gamma_t + \epsilon_{it} \quad (6)$$

$$S_{it} = \alpha i + \beta_1 AI_{it} + \beta_2 SIZ_{it} + \beta_3 (AI_{it} \times SIZ_{it}) + \beta_4 X_{it} + \gamma_t + \epsilon_{it} \quad (7)$$

$$G_{it}=\alpha i + \beta_1 AI_{it} + \beta_2 SIZ_{it} + \beta_3 (AI_{it} \times SIZ_{it}) + \beta_4 X_{it} + \gamma_t + \epsilon_{it} \quad (8)$$

Where ESG_{it} represents Combined ESG score, E_{it} is Environmental score, S_{it} is Social score and G_{it} is Governance score

TABLE 6: RESULTS SUMMARY OF INTERACTION BETWEEN AI INDEX AND FIRM SIZE

Dependent Variable	AI	SIZ	AI × SIZ	R-squared	Significance of Interaction
ESG	1.36**	0.24*	0.38***	0.497	Significant
E	0.82*	0.17	0.29***	0.468	Significant
S	0.74	0.20*	0.22**	0.452	Significant
G	0.61	0.11	0.12 (n.s.)	0.443	Not significant

***p < 0.01, **p < 0.05, *p < 0.1; n.s. = not significant

The interaction term is strongly positive and significant, confirming that the overall ESG impact of AI adoption is greater in larger firms. The moderation effect with Environmental score is significant and sizable, suggesting that large firms are better positioned to apply AI in emissions monitoring, resource efficiency, and sustainable operations. A moderate positive interaction with social score indicates that large firms may utilise AI to enhance labour practices, diversity tracking, and community engagement. However, the base AI effect is not as pronounced. The interaction effect with governance is not statistically significant, indicating that firm size does not significantly influence AI's role in enhancing governance (e.g., board structure, transparency). Governance may be more regulated or standardised across firms regardless of size.

LAGGED AI ADOPTION EFFECTS

To account for the possibility that the influence of AI adoption on ESG performance does not manifest instantaneously, we estimated a lagged-effects model where the AI index was lagged by one year. This approach helps capture delayed impacts that may arise as firms require time to integrate AI into operational processes, decision-making structures, and ESG reporting systems. The estimated model is as follows:

$$ESG_{it} = \alpha_i + \beta_1 AI_{i,t-1} + \beta_2 SIZ_{it} + \beta_3 X_{it} + \gamma_t + \epsilon_{it} \quad (9)$$

Where ESG_{it} is the ESG performance score for firm *i* in year *t*, AI_{it-1} is the AI adoption index of firm *i* in year *t-1*, X_{it} is the Control variables leverage and ROA, γt : Year fixed effects, αi is the firm fixed effects and ϵ_{it} is the Error term.

The coefficient for the lagged AI index remained positive and statistically significant, although slightly smaller in magnitude compared to the contemporaneous model. This result aligns with theoretical expectations that AI's contribution to ESG performance unfolds gradually as AI tools are adopted, refined, and embedded into firm-level ESG strategies. The finding reinforces prior research suggesting that digital transformation, particularly in ESG domains, often experiences delayed returns (Bresciani et al., 2021).

TABLE 7: LAGGED EFFECTS OF AI ADOPTION ON ESG PERFORMANCE

Variable	Coefficient	Std. Error	t-Statistic	p-Value
Lagged AI Index (t-1)	0.043***	0.012	3.58	0.0004
SIZ	0.029**	0.014	2.07	0.038
LEV	-0.015	0.010	-1.50	0.135

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ROA	0.021	0.018	1.17	0.243
Industry & Year Fixed Effects	Yes			
Observations	1000			
R-squared	0.482			

***p < 0.01, **p < 0.05, *p < 0.1

INDUSTRY HETEROGENEITY IN LAGGED AI EFFECTS

To explore potential industry-specific dynamics in the AI–ESG relationship, we extended the lagged model to include interaction terms between the lagged AI index and industry dummies. The model specification is:

$$ESG_{it} = \alpha_i + \beta 1 \ AI_{i,t-1} + j\sum \delta j \ (AI_{i,t-1} \times Industry_j) + \beta_2 \ X_{it} + \gamma_t + \epsilon_{it} \qquad (10)$$

It enables us to estimate the variation in the marginal effect of lagged AI adoption on ESG across industries.

The results show that the base effect of lagged AI remains positive and significant. The interaction terms suggest amplified effects in tech-intensive sectors (e.g., Information Technology, Financial Services), while the effect is weaker or insignificant in resource-intensive sectors (e.g., Energy, Materials). This heterogeneity aligns with prior literature indicating faster digital-ESG integration in knowledge-based industries.

TABLE 8: LAGGED AI × INDUSTRY INTERACTION EFFECTS ON ESG

Variable	Coefficient	Std. Error	t-Statistic	p-Value
Lagged AI (t-1)	0.031**	0.014	2.21	0.027
AI × Information Technology	0.019**	0.009	2.11	0.035
AI × Financial Services	0.023**	0.010	2.30	0.022
AI × Consumer Discretionary	0.015	0.011	1.36	0.174
AI × Healthcare	0.010	0.012	0.83	0.407
AI × Energy	-0.006	0.015	-0.40	0.689
AI × Materials	-0.008	0.014	-0.57	0.570
SIZ	0.027**	0.013	2.08	0.038
LEV	-0.016	0.009	-1.78	0.075
ROA	0.018	0.017	1.06	0.289
Industry & Year Fixed Effects	Yes			
Observations	1000			

R-squared	0.503

***p < 0.01, **p < 0.05, *p < 0.1

DISCUSSION OF RESULTS

The empirical findings of this study provide compelling evidence that Artificial Intelligence (AI) adoption is positively associated with improved ESG performance among Chinese corporations from 2014 to 2023. This section discusses the theoretical and practical implications of these results, situating them within the broader academic literature.

The strong positive relationship between AI adoption and ESG performance (H1) is consistent with Resource-Based View (RBV) theory (Barney, 1991), which posits that firms can achieve competitive advantage by leveraging rare, valuable, and inimitable resources. In this case, AI capabilities act as a strategic asset, enabling firms to manage ESG risks and opportunities more efficiently than traditional systems.

The findings align with Porter and Heppelmann (2014), who argue that innovative, connected technologies transform how firms operate and deliver value, particularly in environmental management and stakeholder engagement. AI-driven automation and analytics help firms track emissions, manage waste, optimise resource use, and thereby meet regulatory and investor expectations for sustainability. This supports earlier work by George et al. (2020), who assert that digital technologies, including AI, are central to advancing corporate sustainability practices.

When ESG is decomposed, the results confirm H2, H3, and H4; AI adoption significantly improves performance across environmental, social, and governance dimensions. AI tools (e.g., real-time sensors, predictive maintenance, and emissions modeling) allow for better environmental monitoring and reporting (Wamba et al., 2021). This aligns with ecological modernisation theory (Mol & Sonnenfeld, 2000), which suggests that technological innovation can resolve ecological challenges without impeding economic growth.

AI enables organisations to assess employee sentiment more effectively, enhance workplace safety, and promote diversity through unbiased recruitment algorithms. These findings extend stakeholder theory (Freeman, 1984), as firms are using technology to meet the expectations of broader constituencies, not just shareholders.

AI contributes to governance by reducing fraud (e.g., AI-driven forensic accounting), improving transparency, and strengthening internal audit functions. This reflects agency theory (Jensen & Meckling, 1976), as AI can reduce information asymmetry between managers and stakeholders.

The interaction analysis shows that the positive impact of AI on ESG is significantly more substantial in large firms than in SMEs. This confirms H5 and aligns with prior empirical studies such as Zubair et al. (2020), who found that large firms are more likely to integrate digital technologies due to greater access to capital, skilled talent, and strategic vision. The Technology-Organisation-Environment (TOE) framework (Tornatzky & Fleischer, 1990) also supports this result: organisational readiness (in this case, firm size) significantly affects technology adoption outcomes.

The evidence gathered in the subsample analysis, as well as the interaction model, strongly supports Hypothesis 5 (H5), which posits that the positive effect of AI implementation on ESG performance is more substantial among larger firms. Namely, the AI index and firm-size interaction effect are positive and statistically different from 0, suggesting that bigger companies benefit more in terms of ESG induced by AI integration than smaller ones.

In disaggregating the ESG score to its three dimensions, Environment (E), Social (S), and Governance (G), the moderating effect of firm size is seen to be strongest in Environmental and Social spaces. These findings indicate that larger companies with better access to digital infrastructure, finances, and experience in dealing with regulations can implement AI in processes such as monitoring emissions, building sustainability in supply chains, diversity analytics, and stakeholder outreach.

In sharp contrast, the impact of AI on Governance outcomes is insensitive primarily to firm size, suggesting that improved governance may be based on rule-based compliance frameworks and institutional norms applied uniformly across firms, regardless of their size.

Altogether, these results confirm the strategic success of large companies in leveraging AI to enhance their ESG performance and highlight the need for policy assistance or capacity development to enable smaller companies to accelerate their ESG performance applications. They also emphasise the necessity of taking organisational context into account, e.g., the size of the firm, when assessing the transformative potential of digital technologies in the ESG context.

The research substantiates H6, indicating that the bidirectional connection between AI and ESG is relatively weak, with significant differences across industries. The greatest impacts have been in the sectors of information technology and financial services, where these players are generally more data-intensive, regulated and publicly monitored.

This diversity encompasses institutional theory (DiMaggio & Powell, 1983), which is based on the idea that firms vulnerable to technologies that complement the concepts of legitimacy and compliance are more likely to experience increased institutional pressure. The more practical ESG outcomes identified in manufacturing and energy relate to AI in smart grids, energy efficiency, emission monitoring, and environmental forecasting.

CONCLUSION

In this paper, Artificial Intelligence (AI) will be explored in its role in improving Environmental, Social, and Governance (ESG) performance in Chinese companies between 2014 and 2023. Against the backdrop of China's evolving sustainability agenda and the country's rapid technological transformation, the results offer new insights into the restructuring of corporate responsibility practices with the aid of AI technologies.

This association was examined between the fixed effect and random effect models, utilising alternative sources of ESG data, and through the omission of outliers, further confirming the stability of the findings.

In addition, with the introduction of a lagged AI index, it was possible to discover that the influence of AI on ESG performance is not instantaneous, but instead it takes time. This finding aligns with existing literature on digital transformation, which emphasises the time-intensive nature of integrating emerging technologies into complex organisational processes.

Notably, the study identified a moderating effect of firm size. Both subsample analyses and interaction models confirmed that larger firms experience a stronger positive impact from ESG considerations related to AI adoption. This is likely due to their greater capacity to invest in AI infrastructure, absorb implementation costs, and align technology use with broader sustainability strategies.

When disaggregating the ESG components, the moderating role of firm size was most pronounced in the Environmental and Social pillars, while Governance outcomes appeared less sensitive to firm scale. These insights highlight the differential pathways through which AI influences ESG dimensions, underscoring the contextual nature of technology-driven sustainability.

From a theoretical standpoint, the study extends the Resource-Based View and dynamic capabilities framework by demonstrating that AI functions as a strategic resource in the context of sustainability transformation. It also reinforces the relevance of institutional theory and the Technology–Organisation–Environment (TOE) framework in explaining how firm characteristics and external pressures shape AI-driven ESG strategies.

Practically, the results underscore the importance of integrating AI into core ESG processes—not only for operational efficiency but also for strategic value creation. Firms that proactively leverage AI for sustainability reporting, emissions tracking, risk governance, and stakeholder engagement are better positioned to meet regulatory standards and societal expectations. From a policy perspective, the uneven adoption of AI across firm sizes and sectors highlights a need for targeted support mechanisms. These may include digital transformation subsidies for SMEs, ESG-AI integration training programs, and industry-specific AI innovation hubs focused on environmental and social outcomes.

In conclusion, as China moves toward a more sustainable and innovation-driven economy, AI will play a critical role in operationalising ESG principles. However, the benefits of this transformation will depend on how inclusively and strategically AI is deployed across the corporate landscape. Future research could explore AI-ESG dynamics in other emerging economies or examine the ethical implications of algorithmic decision-making in ESG domains.

IMPLICATIONS

For managers, these results suggest that investments in AI can yield tangible ESG benefits, particularly when aligned with a firm's capabilities and industry demands. For policymakers, the findings highlight the need for targeted support for SMEs, such as funding for digital infrastructure or ESG reporting tools, to ensure that smaller firms can also benefit from AI-driven sustainability. Lastly, for researchers, the study offers a foundation for further exploration into sector-specific AI applications, cross-country comparisons, and long-term ESG impacts.

In conclusion, AI represents not only a technological innovation but also a strategic lever for enhancing ESG performance, particularly for firms with the scale and resources to harness its potential fully. Bridging the digital divide across firms will be essential for realising the broader sustainability promise of artificial intelligence in the corporate world

LIMITATIONS

While this study provides valuable insights into the relationship between AI adoption and ESG performance, several limitations should be acknowledged.

The AI adoption index, though constructed from publicly available firm-level indicators, may not fully capture the depth, scope, or strategic alignment of AI initiatives within firms. It emphasises presence rather than effectiveness. Additionally, disclosure practices around AI vary widely, potentially leading to measurement bias.

The study primarily relies on ESG scores from Thomson Reuters, with robustness checks using

Bloomberg ESG scores as a complementary source. However, ESG metrics are inherently subjective, and different providers use non-uniform methodologies, which could affect comparability. Moreover, these scores may not fully reflect actual ESG performance, but rather the quality of their reporting.

While addressing concerns about endogeneity in models helps mitigate endogeneity issues, this study is unable to establish causality fully. Reverse causality, where firms with stronger ESG commitments are more likely to adopt AI cannot be ruled out. Instrumental variable approaches could further strengthen causal inference but were beyond the current scope.

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