Artificial Intelligence, A New Engine for ESG Performance

Ruichen Xia[a]

Delaware School of Data Science, Southwestern University of Finance and Economics, Chengdu, 611100, China

[a]xrcthink@UDel.Edu

Abstract. In the past decade, AI has become a major catalyst for enhancing corporate ESG performance and realizing social value. Drawing on data from Chinese A-share listed companies (2010–2022) and theories like resource-based view, information processing, and internal control, this study examines how AI application boosts ESG outcomes. The findings show that AI substantially improves ESG performance, especially in companies with stronger digital infrastructure and operational capabilities. Heterogeneity analysis indicates AI most significantly elevates social responsibility (S), followed by governance (G), while its effect on environmental (E) performance is weaker. The impact is also more pronounced in non-manufacturing and private enterprises. These results offer guidance for companies integrating AI into ESG strategies and for policymakers seeking to align AI initiatives with sustainable development goals and differentiated policies.

Keywords: Artificial Intelligence; ESG; Digital Infrastructure; Corporate Operations.

1. Introduction

Over the past decade, AI has propelled economic and societal progress through its powerful data processing and autonomous learning capabilities. In industrial production, AI has catalyzed “smart manufacturing,” improving automation and resource efficiency while advancing green transformation. In transportation and logistics, intelligent scheduling systems, autonomous vehicles, and smart warehousing have significantly reduced energy consumption and carbon emissions, injecting new vitality into sustainable growth. China has also placed substantial emphasis on AI development. On July 4, 2024, Premier Li Qiang attended the opening of the 2024 World Artificial Intelligence Conference and the High-Level Meeting on Global Governance of Artificial Intelligence in Shanghai, underscoring China’s commitment to intelligent transformation, AI innovation, and the global governance of AI security.

Against this backdrop, the deep application of artificial intelligence is becoming a new engine for improving ESG (Environmental, Social, and Governance) performance. ①Walmart has collaborated with IBM to use the AI platform Envizi in tracking the carbon footprint of its supply chain, achieving real-time monitoring of carbon emissions data for 85% of its suppliers. ②Schneider Electric has launched a new energy management optimization solution, utilizing the AI-driven EcoStruxure system to help client companies reduce energy consumption by an average of 30%. ③Alibaba developed and deployed the AI auditing robot "Ali Tianxun" to automatically check the compliance of internal financial processes, resulting in a remarkable 55% year-on-year decrease in internal fraud cases in 2023. ④Deloitte reported that AI in logistics and warehousing lowers energy use by 15% while improving inventory management, reducing pollution, and enhancing supply-chain transparency. The processes in these examples illustrate the positive impact of artificial intelligence on improving corporate ESG performance.

Existing research lacks systematic examination of how AI affects corporate ESG performance. Most studies view AI purely as a digital tool for efficiency or competitiveness, neglecting environmental, social, and governance aspects. They often rely on case studies or qualitative analysis, lacking large-scale empirical data. Technical barriers, data constraints, and measurement challenges further limit understanding. Given AI’s potential in resource allocation, supply chain transparency, and risk management, this gap must be addressed. Accordingly, this paper investigates whether AI can effectively tackle ESG challenges to enhance corporate performance and explores the underlying mechanisms, providing empirical insights for more feasible ESG strategies.

The marginal contributions of this paper are twofold:

Theoretically, it expands ESG research beyond governance structures and financial indicators by incorporating AI application, validating through empirical tests how AI enhances ESG performance. It also establishes the moderating roles of digital infrastructure and operational capabilities in this process, with multi-dimensional robustness tests (e.g., instrumental variables, industry clustering) confirming the findings.

Practically, it offers guidance for firms to strengthen digital infrastructure and organizational capabilities rather than relying solely on technology procurement. Policymakers can design differentiated policies based on revealed industry heterogeneity, and investors can use AI–ESG links—such as ethical AI committees and smart environmental equipment adoption—to pinpoint long-term investment prospects.

2. Theoretical Analysis

AI, as a scarce strategic resource, can help companies gain a differentiated advantage in ESG performance through its inimitability and non-substitutability (Barney, 1991) [3]. Its high technical barriers, development costs, and limited talent pool make it hard to replicate. Furthermore, AI improves decision-making by enhancing information acquisition and processing (Galbraith, 1974) [14]; for example, it can monitor supply chain risks in real-time, aiding companies in meeting environmental and social responsibilities (Waller & Fawcett, 2013) [30].

AI also strengthens internal control, risk management, and compliance (May, 1993) [21], helping firms identify and address ESG threats proactively, automate compliance monitoring, and boost transparency. However, its benefits are not automatic. Without the right capabilities and infrastructure, firms risk falling into a "technology trap," where heavy investment fails to yield expected returns (Teece, Pisano, & Shuen, 1997) [27].

Accordingly, we propose twofold hypothesis H1:

H1a: The application of artificial intelligence helps to improve corporate ESG performance.

H1b: The application of artificial intelligence has no positive effect on corporate ESG performance.

AI's impact on ESG performance depends on operational capabilities such as optimizing management processes, promoting cross-departmental collaboration, and enabling flexible resource allocation. According to complementary assets theory (Teece, 1986) [26], new technology must align with existing resources and capabilities to unlock its full value. Strong operational capabilities help companies apply AI to critical decision-making, achieving precise ESG management. On the other hand, insufficient operational capabilities may lead to misused technical resources and limited ESG improvements.

Dynamic capabilities theory (Teece et al., 1997) [27] offers another perspective, emphasizing the need for firms to continuously integrate, build, and reconfigure internal and external resources in response to a rapidly changing environment. Operational capabilities act as a moderating mechanism that helps companies flexibly leverage AI, ensuring ongoing ESG value creation and adaptation.

Accordingly, we propose hypothesis H2:

H2: Operational capability positively moderates the effect of AI application on ESG performance, meaning that higher operational capability amplifies the ESG benefits of the same degree of AI application.

A strong digital infrastructure is crucial for AI adoption. According to the TOE framework (Tornatzky & Fleischer, 1990) [28], factors like data collection, storage, and transmission significantly influence technology implementation. With robust cloud platforms, scalable computing power, and stable networks, companies can develop and deploy AI faster and at lower cost. Conversely, insufficient digital preparation impairs AI's ability to meaningfully support environmental, social, and governance initiatives, ultimately limiting organizational effectiveness.

Accordingly, we propose hypothesis H3:

H3: A high level of digital infrastructure positively moderates AI’s impact on ESG performance, meaning that stronger digital infrastructure drives greater ESG improvements from the same degree of AI use.

3. Research Design

(1) Sample Selection and Data Sources

This study examines A-share listed companies in China (2010–2022), excluding those in finance/real estate, ST/*ST firms, and those with missing or abnormal data, yielding 13,051 observations. Key data come from CSMAR and Wind, with missing values supplemented from annual reports. All continuous variables are winsorized at the 1% and 99% levels, and Stata 18.0 is used for data processing and analysis.

(2) Variable Selection

1. Corporate ESG Level

This study uses Bloomberg ESG ratings to measure the ESG performance of A-share listed companies, given Bloomberg’s broad coverage and rigorous methodology. Each dimension (Environmental, Social, Governance) receives a score out of 100 based on disclosed information, with weights adjusted for industry differences, yielding a final weighted ESG score. For robustness, the Huazheng ESG score is also used as an alternative benchmark.

2. Degree of Artificial Intelligence Application

This study measures corporate AI application by referencing Yao Jiaquan (2024) [45], who uses Python to scrape AI-related keywords from the “Management Discussion and Analysis” sections of annual reports. The keyword frequency is adjusted (adding one) and then log-transformed to produce the i_MDA indicator. Additionally, following Wu Fei et al. (2022) [42], this study extracts the frequency of “artificial intelligence” mentions and applies the same logarithmic transformation, resulting in wflni as a robustness measure.

3. Level of Digital Infrastructure

This study measures digital infrastructure by referencing and adjusting the approach of Sun Wenyuan et al. (2023)[40], who used the per capita value of machinery and equipment (i.e., book value of machinery in the fixed asset statement divided by total employees) as an indicator of AI adoption. While this may overlook software investment and talent factors, it effectively captures hardware investment scale and company size differences, making it suitable as a moderating measure of digital infrastructure. Based on its English abbreviation (digital infrastructure level), the variable is denoted as DIL.

4. Company Operational Capability

To measure corporate operational capability, this study references the work of Sun Bei et al. (2023)[39], using total asset turnover as the measurement indicator. Total asset turnover refers to the ratio of a company's operating revenue to its average total assets over a certain period. A higher total asset turnover indicates that a company can reasonably utilize internal funds, reflecting a more rational internal structure and stronger operational capability. This study collected asset turnover data for A-share listed companies from 2010 to 2022, denoting the operational capability variable using the English abbreviation OC.

5. Control Variables

Based on existing relevant research, the following control variables are set: debt-to-asset ratio (Lev), company size (Size), return on assets (ROA), return on equity (ROE), board size (Board), inventory ratio (INV), fixed asset ratio (FIXED), and revenue growth rate (Growth). Specific variable names and definitions are provided in Table 1 below:

Table 1 Controls and description

definition	variable	description
debt-to-asset ratio	Lev	Total Liabilities / Total Assets
company size	Size	Natural Logarithm of Total Assets
return on assets	ROA	Net Income / Average Total Assets
return on equity	ROE	Net Income / Average Shareholders' Equity
board size	Board	Natural Logarithm of the Number of Board Members
inventory ratio	INV	Net Inventory / Total Assets
fixed asset ratio	FIXED	Net Fixed Assets / Total Assets
revenue growth rate	Growth	Current Year Revenue / Previous Year Revenue - 1

(3) Model Construction

This study aims to explore the impact of artificial intelligence applications on corporate ESG performance and further analyze the role of moderating variables such as the level of digital infrastructure and corporate operational capabilities. Considering that this research is based on panel data, a two-way fixed effects model is employed for regression analysis to mitigate potential omitted variable issues and control for unobservable heterogeneity across time and individuals, thereby investigating the aforementioned hypotheses.

To explore hypothesis H1, we construct model (1).

$$\begin{aligned} ESG_{it} = {} & \beta_0 + \beta_1 i\_MDA_{it} + \beta_2 Lev_{it} + \beta_3 Size_{it} + \beta_4 ROA_{it} + \beta_5 ROE_{it} + \beta_6 Board_{it} + \beta_7 INV_{it} \\ & + \beta_8 FIXED_{it} + \beta_9 Growth_{it} + \mu_{i1} + \lambda_{t1} + \varepsilon_{it} \end{aligned} \tag{1}$$

For H2 and H3, we construct model (2) and (3), correspondingly.

$$\begin{aligned} ESG_{it} = {} & \alpha_0 + \alpha_1\, i\_MDA_{it} + \alpha_2\, OC_{it} + \alpha_3\, c\_i\_MDA_{it} \times c\_OC_{it} + \alpha_4 Lev_{it} + \alpha_5 Size_{it} \\ & + \alpha_6 ROA_{it} + \alpha_7 ROE_{it} + \alpha_8 Board_{it} + \alpha_9 INV_{it} + \alpha_{10} FIXED_{it} + \alpha_{11} Growth_{it} \\ & + \mu_{i2} + \lambda_{t2} + \delta_{it} \end{aligned} \tag{2}$$

$$\begin{aligned} ESG_{it} = {} & \gamma_0 + \gamma_1\, i\_MDA_{it} + \gamma_2\, DIL_{it} + \gamma_3\, c\_i\_MDA_{it} \times c\_DIL_{it} + \gamma_4 Lev_{it} + \gamma_5 Size_{it} \\ & + \gamma_6 ROA_{it} + \gamma_7 ROE_{it} + \gamma_8 Board_{it} + \gamma_9 INV_{it} + \gamma_{10} FIXED_{it} + \gamma_{11} Growth_{it} + \mu_{i3} \\ & + \lambda_{t3} + \theta_{it} \end{aligned} \tag{3}$$

For the models above, i represents the enterprise, t denotes the year, μ_i, λ_t represent the individual effects of the enterprise and the time effects, respectively. $\varepsilon_{it}, \delta_{it}, \theta_{it}$ represent the random disturbance terms of each model. β_1 is the key parameter for exploring hypothesis H1. If β_1 is significantly greater than 0, it indicates that hypothesis H1a is valid. Conversely, if β_1 is not significantly greater than 0, hypothesis H1b is valid.

To investigate the moderating effect, we first center the variables i_MDA_{it}, OC_{it}, creating the variables $c\_i\_MDA_{it}, c\_OC_{it}$. We then establish the interaction term $c\_i\_MDA_{it} \times c\_OC_{it}$ as the core variable for exploring hypothesis H2. If α_1, α_3 are significantly positive, it indicates that hypothesis H2 is valid. Similarly, we create the variables $c\_i\_MDA_{it}, c\_DIL_{it}$, and establish the interaction term $c\_i\_MDA_{it} \times c\_DIL_{it}$. If γ_1, γ_3 are significantly positive, it indicates that hypothesis H3 is valid.

4. Empirical Analysis

(1) Descriptive Statistics

Table 2 shows descriptive statistics for key variables. The mean ESG is 28.57 (SD = 9.784; min = 6.198; max = 71.18), indicating wide disparities in sustainability and social responsibility. The mean AI application level is 0.705 (SD = 1.088; range = 0 ~ 4.691), reflecting uneven adoption among firms. Operational efficiency averages 0.640 (SD = 0.432; range = 0.0546 ~ 2.907), suggesting moderate variation. Digital infrastructure averages 207,588 (SD = 389,306; range = 0 ~ 2,729,000), demonstrating significant differences in firms' digital investment.

Table 3 presents Pearson correlations, mostly consistent with expectations. ESG shows a significant positive correlation with AI usage (i_MDA) and digital infrastructure (DIL). AI usage (i_MDA) is also significantly positively correlated with DIL and operational capability (OC). Correlation coefficients among explanatory and control variables remain generally low, except for a close relationship between ROA and ROE, indicating no severe multicollinearity.

Table 2 Descriptive Statistics Results

variable	sample size	average	s.d.	min	max
Size	45,030	22.16	1.304	19.41	26.44
Lev	45,030	0.415	0.208	0.0274	0.925
ROA	45,029	0.0410	0.0668	-0.375	0.254
ROE	44,982	0.0622	0.136	-0.962	0.420
OC	45,025	0.640	0.432	0.0546	2.907
INV	44,671	0.140	0.129	0	0.778
FIXED	45,029	0.204	0.157	0.00160	0.765
Growth	45,005	0.154	0.387	-0.653	3.808
Board	44,971	2.117	0.199	1.609	2.708
ESG	13,232	28.57	9.784	6.198	71.18
i_MDA	44,662	0.705	1.088	0	4.691
DIL	30,120	207,588	389,306	0	2.729e+06

Table 3 Correlation Matrix of Key Variables

variable	ESG	i_MDA	DIL	OC	Lev	Size	ROA	ROE	Board	INV	FIXED
i_MDA	0.221***										
DIL	0.140***	-0.121***									
OC	0.003	-0.044***	-0.092***								
Lev	0.068***	-0.100***	0.147***	0.142***							
Size	0.477***	-0.012**	0.291***	0.047***	0.494***						
ROA	-0.006	-0.045***	-0.040***	0.191***	-0.377***	-0.022***					
ROE	0.008	-0.049***	-0.010*	0.213***	-0.228***	0.080***	0.895***				
Board	-0.015*	-0.115***	0.088***	0.026***	0.152***	0.254***	0.013***	0.044***			
INV	-0.110***	-0.109***	-0.186***	0.062***	0.297***	0.105***	-0.064***	0.018***	-0.005		
FIXED	0.012	-0.256***	0.501***	0.010**	0.111***	0.115***	-0.077***	-0.058***	0.145***	-0.269***	
Growth	-0.009	-0.019***	0.024***	0.146***	0.036***	0.041***	0.255***	0.262***	0.009*	0.044***	-0.049***

(2) Regression Analysis

Table 4 reports the benchmark regressions and moderating effects. In Column (1), the coefficient for the AI application level (i_MDA) is 0.208 (>0), significant at the 1% level, thus rejecting H1b and supporting H1a—indicating that AI usage enhances ESG performance. In Column (2), i_MDA remains positively significant, and the interaction term (c_DIL×c_i_MDA) is also positive and significant at the 1% level, confirming H2; notably, DIL itself is significantly positive at the 1% level, further aligning with existing evidence that digital infrastructure enhances ESG. In Column (3), i_MDA is again positively significant, and the interaction term (c_OC×c_i_MDA) is positive and significant at the 1% level, validating H3 by showing that corporate operational efficiency positively moderates the AI–ESG relationship.

Table 4 Regression results

variable	(1) ESG	(2) ESG	(3) ESG
i_MDA	0.208***	0.266***	0.194**
	(-2.72)	(-2.9)	(-2.55)
c_DIL×c_i_MDA		0.000***	
		(-3.13)	
c_OC×c_i_MDA			0.371***
			(-2.79)
OC			0.521**
			(-2.55)
DIL		0.000***	
		(-6.24)	
Lev	-3.329***	-3.166***	-3.444***
	(-6.99)	(-5.55)	(-7.20)
Size	1.352***	1.275***	1.376***
	(-12.89)	(-10.1)	(-12.96)
ROA	3.847**	1.577	3.177*
	(-2.03)	(-0.7)	(-1.66)
ROE	1.09	1.688*	1.081
	(-1.37)	(-1.79)	(-1.36)
Board	0.024	0.522	0.035
	(-0.06)	(-1.2)	(-0.1)
INV	2.699***	3.107***	2.624***
	(-3.78)	(-3.65)	(-3.66)
FIXED	1.965***	0.114	1.982***
	(-3.43)	(-0.15)	(-3.46)
Growth	0.033	0.045	-0.006
	(-0.32)	(-0.36)	(-0.06)
Year	YES	YES	YES
Firm FE	YES	YES	YES
Constant	-11.688***	-11.288***	-12.499***
	(-5.02)	(-4.02)	(-5.27)
Observations	13,051	9,778	13,051
R-squared	0.724	0.729	0.724
F-test	0	0	0
r2_a	0.689	0.689	0.69
F	1381	955.8	1268

The values in parentheses represent the t-statistics adjusted for robust standard errors at the enterprise level; the symbols "*", "**", and "***" indicate significance at the 10%, 5%, and 1% levels, respectively.

(3). Endogeneity Test

Firms that perform well in sustainable areas such as ESG often possess greater capabilities and resources to enhance their AI technology investments, leading to a reverse effect of ESG performance on AI investments. In other words, the degree of AI application and ESG performance may mutually influence each other, making it difficult to exclude reverse causality through unidirectional regression, thus resulting in endogeneity issues. Therefore, this paper references the study by Zhang Xuan et al. (2019) [47]and selects the degree of AI application in the same industry for the same year as an instrumental variable. Using two-stage least squares estimation, we conduct an endogeneity test, denoting the instrumental variable as "instrument." The selection of the instrumental variable is based on two considerations: first, the overall level of AI application in the industry in the same year often reflects the average level of technology use or development trends within that industry. The diffusion of new technologies at the industry level can create a "demonstration effect" or "follow-up effect," leading to a certain degree of correlation and similarity in AI application levels among firms within the same industry. Therefore, the degree of AI application in the same industry for the same year is often highly correlated with the firm's own degree of AI application, satisfying the relevance requirement for the instrumental variable. Second, the average level of AI application in the same industry does not directly affect a specific firm's ESG performance; rather, it influences the firm's own degree of AI application, which in turn affects ESG performance. In other words, the ESG level of a single firm is not sufficient to significantly disrupt the overall AI development trend or average level within the industry, allowing the degree of AI application in the same industry for the same year to be considered relatively exogenous. As long as appropriate industry and time fixed effects are controlled, the overall industry level generally should not have a systematic association with unobservable characteristics of a specific firm (such as management preferences, corporate culture, etc.), thus satisfying the exogeneity requirement for the instrumental variable.

Table 5 presents the regression results from the two-stage least squares method. The first stage regression results indicate that the instrumental variable has a positive impact on the firm's degree of AI usage, which is significant at the 1% level, consistent with the previous theoretical analysis. In the second stage regression, the regression coefficient for ***IV-i_MDA*** is 4.92 > 0, and it is also significant at the 1% level. Additionally, the weak instrument test yields F = 6163, which is far greater than the empirical critical value of 10, rejecting the weak instrument hypothesis. These results suggest that the endogeneity issues arising from potential reverse causality between the degree of AI application and the firm's ESG performance have a minimal impact on the findings of this study, and the aforementioned conclusions remain robust.

Table 5 Instrumental Variable Regression Results

variable	First-stage	Second-stage
	i_MDA	ESG
instrument	1.00*** (78.51)	
IV-i_MDA		4.92*** (32.73)
Controls	YES	YES
R-squared	0.4012	0.2199

(4). Robustness Test

1. Replacement of Core Variables

First, we use different measurement methods for the dependent variable, employing Huazheng ESG as the sample data for ESG, denoted as ***hz_ESG***, while keeping other variables constant. Secondly, we replace the core explanatory variable ***i_MDA***, referencing the research by Wu Fei et al. (2022)[42], to construct the variable ***wflni*** to reassess the level of adoption of artificial intelligence, again holding other variables unchanged. As shown in Table 6, i_MDA remains significant at the 1% level when hz_ESG is used. After substituting i_MDA with wflni, its coefficient is still significantly positive at the 5% level. These results demonstrate the model’s robustness under alternative ESG and AI measures.

Table 6 Robustness Test of Core Variable Replacement

Variable	(1) hz_ESG	(2) ESG
i_MDA	0.054***	
	(-9.08)	
wflni		0.178**
		(-1.97)
Constant	-0.101	-12.394***
	(-0.54)	(-5.31)
Controls	YES	YES
Year	YES	YES
Firm FE	YES	YES
Observations	43,555	13,139
R-squared	0.051	0.725
F-test	0	0
r2_a	-0.0777	0.691
F	90.16	1399

2. Attempting Different Combinations of Control Variables

To avoid the main model being significant only under specific combinations of control variables, this study explores various combinations of control variables. Group (a) of control variables remains consistent with those in Model (1). The combinations for groups (b) and (c) are presented in Table 7 below:

Table 7 Control variables for (b) and (c)

b	Variable Definition	Construction Description	c	Variable Definition	Construction Description
Loss	Whether Loss	1 if net profit is less than 0, otherwise 0	Employ	Number of Employees	Total number of employees
Board	Board Size	Natural logarithm of the number of board members	Cap1	Capital Intensity	Total assets / Number of employees
Indep	Proportion of Independent Directors	Independent directors / Total number of directors	Pay	Executive Salary Incentives	Natural logarithm of total annual salary of management
Dual	Dual Role	1 if the chairman and CEO are the same person, otherwise 0	Occupy	Major Shareholder Fund Occupation	Other receivables / Total assets
Top1	Proportion of Largest Shareholder	Number of shares held by the largest shareholder / Total shares	Big4	Audit Status	1 if audited by one of the Big Four (PwC, Deloitte, KPMG, EY), otherwise 0
Balance1	Equity Balance Degree	Proportion of shares held by the second-largest shareholder / Proportion of shares held by the largest shareholder	FirmAge	Company Age	ln(Current Year - Year Established + 1)
TobinQ	Tobin's Q Value	Market value / Replacement cost of assets	INST	Proportion of Institutional Investors	Total shares held by institutional investors / Circulating shares
ListAge	Listing Age	ln(Current Year - Year Listed + 1)	Mshare	Management Shareholding Ratio	Shares held by management / Total shares

Regression analyses were conducted for groups (b) and (c), with results presented in Table 8. Table 8 shows the regression results for groups (b) and (c). In group (b), i_MDA is positively significant at the 1% level; in group (c), it is positively significant at the 5% level, confirming the results remain robust despite changes in control variables.

Table 8 Robust test for different group of controls

Group	a	b	c
variable	ESG	ESG	ESG
i_MDA	0.208***	0.263***	0.174**
	(-2.72)	(-3.47)	(-2.29)
Firm FE	YES	YES	YES
Year	YES	YES	YES
Observations	13,051	13,138	12,505
R-squared	0.724	0.72	0.724
F-test	0	0	0
r2_a	0.689	0.685	0.688
F	1381	1365	1321

5. Heterogeneity Analysis

(1) Heterogeneity of the Three Dimensions of ESG

By leveraging AI-enabled data analysis and machine learning, enterprises can rapidly integrate feedback data, thereby improving customer service, enhancing employee experiences, and acquiring deeper insight into consumer needs. These enhancements primarily benefit the social (S) dimension of ESG, exemplified by AI-based personalized recommendation systems that boost customer satisfaction and intelligent HR systems that enrich the employee experience. However, because environmental (E) developments often require complex regulatory compliance and have extended investment return cycles, many firms rely on traditional methods, limiting AI's immediate impact on the environmental dimension. Regarding governance (G), AI supports transparent and accountable decision-making, yet factors such as cultural adaptation, internal resistance, and skill shortages slow its full realization. Consequently, the relative influence of AI across ESG ranks S > G > E.

To examine the differences in AI's impact on enterprises' ESG performance across the E, S, and G dimensions, this study uses the corresponding Bloomberg ESG sub-scores (BloombergE, BloombergS, BloombergG) as dependent variables. Table 9 reveals that: (1) For governance (G), i_MDA is positively significant at the 10% level, indicating a modest beneficial effect. (2) For the social (S) dimension, i_MDA demonstrates robust significance (1% level), confirming that AI substantially enhances social performance. (3) For the environmental (E) dimension, i_MDA is not significantly positive, suggesting a relatively weaker influence of AI on environmental performance. These findings align with the statemant that AI's impact follows the order S > G > E.

Table 9 Test for the Heterogeneity of ESG Across Dimensions

variable	(1) BloombergG	(2) BloombergS	(3) BloombergE
i_MDA	0.201*	0.319***	0.028
	(1.74)	(3.88)	(0.19)
Controls	YES	YES	YES
Firm FE	YES	YES	YES
Year	YES	YES	YES
Constant	49.410***	-35.476***	-49.847***
	(14.02)	(-14.19)	(-11.39)
Observations	13,051	12,938	12,854
R-squared	0.740	0.458	0.413
F-test	0	0	0
r2-a	0.740	0.458	0.413
F	1501	441.6	366.2

(2) Heterogeneity of Property Rights Characteristics

Due to the different nature of property rights, enterprises face diverse policy orientations and market conditions, leading to varied impacts of AI on ESG performance. Private enterprises, generally more flexible and responsive to stakeholder demands, adopt proactive ESG measures more readily, benefiting from greater decision-making autonomy and faster innovation. In contrast, state-owned enterprises often encounter policy constraints and bureaucratic processes, slowing their ESG responses. Consequently, AI's effect on ESG performance is more pronounced for private enterprises than for state-owned enterprises.

Variable SOE is introduced (1 for state-owned, 0 for private) to examine how property rights affect AI's impact on ESG performance. The sample splits into two subsamples for group regression; Table 10 shows that i_MDA in column (3) is significantly more impactful than in column (4), affirming the earlier analysis.

(3). Analysis of Industry Characteristics Heterogeneity

From the perspective of industry characteristics, compared to traditional manufacturing, the non-manufacturing sector relies more on data analysis in its operations and decision-making processes, resulting in a more flexible decision-making approach (Waller & Fawcett, 2013). The involvement of artificial intelligence (AI) provides strong support for decision-making in the non-manufacturing sector, enabling rapid analysis of customer behavior and market trends, which assists companies in formulating sustainable development strategies (Davenport & Ronanki, 2018). For instance, the retail and financial industries utilize AI to analyze customer preferences, allowing for more effective adjustments to products and services, thereby achieving sustainable growth (Chen, Chiang, & Storey, 2012).

The non-manufacturing sector generally places a higher emphasis on social responsibility and customer relations, which gives it an advantage in the impact of AI on ESG performance. With the introduction of AI, the non-manufacturing sector can quickly obtain and process customer feedback, enhancing customer experience and satisfaction (Kotler & Lee, 2005). In contrast, the manufacturing sector faces more structural challenges in social responsibility and environmental management (Friede, Busch, & Bassen, 2015), which limits the application of AI. Therefore, this paper posits that the impact of AI on ESG performance is significantly greater in the non-manufacturing sector than in manufacturing.

To verify industry-related heterogeneity, enterprises are classified using their industry codes based on the method of China's National Economic Industry Classification, with B and E indicating manufacturing. Two subsamples (B or E vs. non-B/E) are regressed. Table 10 shows that i_MDA in column (1) is notably more significant than in column (2), confirming the earlier heterogeneity analysis.

Table 10 Heterogeneity of Industry Characteristics and Property Rights Characteristics

Variable	(1) ESG	(2) ESG	(3) ESG	(4) ESG
	Non-Manufacturing Industry	Manufacturing Industry	SOE = 0	SOE = 1
i_MDA	0.487***	0.229**	0.232**	0.196*
	(4.24)	(2.33)	(2.26)	(1.72)
Constant	4.124	-17.573***	-18.571***	-8.693**
	(1.00)	(-5.95)	(-5.71)	(-2.49)
Controls	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Year	YES	YES	YES	YES
Observations	3,745	9,306	6,147	6,904
R-squared	0.703	0.734	0.685	0.754
Ftest	0	0	0	0
r2_a	0.660	0.699	0.638	0.728
F	352.2	1031	528.0	868.1

6. Literature References

In the past decade, research on the influencing factors of ESG has become relatively abundant. Based on mainstream research directions, these factors can be categorized into internal and external factors. From an internal perspective, company characteristics, financial performance, corporate governance, and executive characteristics are the most frequently studied influencing factors. Larger companies tend to invest more in ESG (Drempetic et al., 2020) [11]; non-family-controlled companies are more likely to have higher ESG performance (Beji & Loukil, 2021) [4]; strategic activities such as multinational operations, mergers and acquisitions, technological innovation, and R&D investment can improve ESG performance (Maniora, 2015; Mervelskemper & Streit, 2017) [19][22]. The impact of financial performance remains controversial, with some studies finding a positive correlation between financial performance and ESG (Cai et al., 2016) [5], while others have found no significant association (Garcia et al., 2017) [15], or inconsistent results (Crace & Gehman, 2022) [9]. Simultaneously, female directors or diverse backgrounds contribute to ESG improvement (Garcia–Blandon et al., 2019) [16]; CEO personal background, incentive mechanisms (Kang, 2017) [13], and leadership styles (Crace & Gehman, 2022) [9] can impact ESG; establishing sustainability/CSR committees and adopting systematic management (e.g., ISO) can improve ESG performance (Chevrollier et al., 2019; Beji & Loukil, 2021) [8][4]. From an external perspective, national institutions and culture, regulation and economic development level, and industry attributes are the main influencing factors. Some studies indicate that stronger political rights lead to more proactive ESG engagement by companies (Cai et al., 2016; Attig et al., 2016; Umar et al., 2020) [5][2][29], but there are also opposing views (Mooneeapen et al., 2022) [23]; different national cultures and informal institutions can influence corporate sustainability strategies (Foo Nin et al., 2012; Cai et al., 2016) [12][5]. Research on Chinese companies shows that environmental regulations can positively (Wang et al., 2022) [31] or negatively (Shu & Tan, 2023; Yan et al., 2023) [25][32] affect ESG, and this cannot be easily generalized to other countries. Concurrently, the level of economic development and financial crises often influence the direction of corporate ESG investments (Cassely et al., 2021; Foo Nin et al., 2012) [6][12]. Furthermore, some studies consider industry attributes as a strong external driver (Crace & Gehman, 2022; Arminen et al., 2017) [9][1], while others believe their impact is limited (Short et al., 2015) [24]. However, in the literature that treats ESG as a whole research object, there is little mention of the recently emerging artificial intelligence.

Currently, the potential of AI to improve corporate environmental performance (E), undertake social responsibility (S), and enhance governance efficiency (G) has been initially verified. In the E dimension, empirical studies show that artificial intelligence has a significant role in improving environmental performance and promoting green development. On the one hand, the application of artificial intelligence helps to improve resource utilization efficiency and reduce industrial carbon emission intensity (Xu Xiaodan & Hui Ning, 2024) [44]; on the other hand, artificial intelligence can improve the performance of the E dimension by stimulating green technology innovation and optimizing industrial structure. This effect is not only reflected in technological innovation in the industrial production process, but also in the comprehensive green transformation support for enterprises from the organizational level to the strategic decision-making level (Lü Yue et al., 2023) [38]. In the S dimension, artificial intelligence plays a vital role in optimizing product and service quality advantages and reducing external information asymmetry, indicating that AI applications can not only improve the quality of the product itself, but also further enhance the overall competitiveness of the enterprise by improving customer relations and expanding market structure (Zhong Juan et al., 2024) [48]; through data-driven supplier selection and evaluation, real-time collaboration platform construction, and digital decision-making mechanisms, companies can conduct supplier management more objectively and fairly (Dai Zhixiang, 2024; Han Yonggang, 2024) [34][36], which not only helps to improve operational efficiency and reduce risks, but also creates a more fair and transparent working environment for suppliers and internal employees. In the G dimension, the application of AI can not only improve the efficiency of corporate financial data processing, but also achieve a qualitative leap in internal control, risk management, and decision support (Gao Linyan, 2025) [35]; at the same time, AI also plays a certain role in improving audit efficiency, ensuring data quality, and reducing human errors. AI-assisted auditing can improve the accuracy of internal control, further strengthen the overall governance structure of the enterprise, and improve transparency and standardization (Zhang Wei, 2025) [46].

Although there is evidence to prove the impact of AI on certain dimensions of ESG performance by disaggregating ESG into three dimensions, there is a lack of research exploring the correlation between the two with overall ESG performance as the explained variable. A relatively representative study in the existing literature is that of Xu Jiayun et al. (2024) [43], which empirically concludes that the development of artificial intelligence significantly improves the overall ESG performance of A-share listed companies, and that artificial intelligence mainly plays a role through three channels: improving the level of corporate green technology innovation, total factor productivity, and corporate information transparency. Zhu Siwei et al. (2024) [50], when studying the impact of artificial intelligence on corporate social performance, used ESG performance as an indicator to measure the dependent variable, and also verified the positive impact of AI on ESG performance, and used whether to assume corporate digital responsibility as a moderating mechanism. At the same time, studies have shown that AI has a positive impact on the ESG performance of the financial industry, and the level of technological innovation can be selected as an intermediary variable, and the uncertainty of economic policies can be regarded as a negative moderating mechanism (Tong Jian, 2024) [41]. ESG not only appears in the literature as an explained variable, but also as an intermediary variable. For example, when exploring the impact of AI on the level of green governance, the ESG performance of enterprises is used as an intermediary variable, and AI promotes the improvement of the level of green governance by optimizing the ESG performance of enterprises (Zhu Li & Jiang Wenqi, 2024) [49], which also indirectly shows that there is a correlation between AI and ESG performance. The role of AI on ESG performance is not only limited to ESG performance itself, but can also affect the investment status of enterprises in ESG (Huang Dong, 2024) [37]. In addition, AI also plays an important role in the ESG rating process, which mainly plays a role by optimizing the rating model, assisting data analysis, reducing costs, and real-time monitoring, making the rating process more scientific and reasonable (Che Xiaoli & Hu Qingyu, 2024) [33].

Despite growing research on AI’s overall impact on ESG, existing studies often focus on narrow industries, rely on macro-level variables that overlook internal factors, or treat ESG as a substitute for social performance, limiting mechanism analysis. Some studies also concentrate on industries with minimal environmental impacts, reducing the significance of exploring environmental heterogeneity. This paper aims to address these gaps by synthesizing current work, offering detailed theoretical frameworks and mechanisms, and illustrating the moderating role of enterprises' internal environmental factors.

7. Summary

Finally, to conclude the article and give some advice.

This study selects A-share listed companies as the research sample. The findings indicate that the use of artificial intelligence (AI) contributes to improving corporate ESG performance. In this process, the level of digital infrastructure and corporate operational capabilities play a positive moderating role. Robustness and endogeneity tests confirm the reliability of the research results. Additionally, heterogeneity analysis reveals that the significance of AI's impact on the various dimensions of ESG is in the order of S > G > E, with AI's role in enhancing ESG being more pronounced in non-manufacturing and private enterprises.

Based on these findings, the following recommendations are made for enterprises and the government:

For enterprises, it is essential to fully integrate AI into their ESG strategies, closely aligning the application of AI technology with their ESG objectives. Companies should clearly define specific application scenarios for AI in environmental management, social responsibility, and corporate governance, and develop corresponding implementation plans. Furthermore, investment in digital infrastructure should be increased to ensure robust data integration and analytical capabilities, thereby maximizing AI's potential to enhance ESG performance. Additionally, attention should be paid to the compatibility between the company's operational capabilities and the degree of AI application, selecting the level of AI use that aligns with their operational conditions.

For the government, it is important to recognize the positive impact of AI usage on ESG performance and actively create conditions for AI to improve ESG outcomes. This includes increasing investment in digital infrastructure, particularly for small and medium-sized enterprises, to ensure they have access to necessary technical support and resources. A clear policy framework should be established and adopted to encourage companies, especially in non-manufacturing and private sectors, to actively adopt AI technology to enhance their ESG performance. Financial subsidies and tax incentives could also be provided to reduce the costs associated with innovative AI applications. Moreover, attention should be given to the heterogeneity arising from industry and ownership characteristics in order to formulate differentiated policies.

References

[1] References (sorted by alphabetical order and Chinese articles are listed behind)

[2] Arminen, H., Puumalainen, K., Pätari, S., Fellnhofer, K., 2017. Corporate social performance: inter-industry and international differences. J. Clean. Prod., 177(3), 426–437.

[3] Attig, N., Boubakri, N., El Ghoul, S., Guedhami, O., 2016. Firm internationalization and corporate social responsibility. J. Bus. Ethics, 134(2), 171–197.

[4] Barney, J., 1991. Firm Resources and Sustained Competitive Advantage. Journal of Management, 17(1), 99–120.

[5] Beji, R., Loukil, N., 2021. Board diversity and corporate social responsibility: empirical evidence from France. J. Bus. Ethics, 173(1), 133–155.

[6] Cai, Y., Pan, C.H., Statman, M., 2016. Why do countries matter so much in corporate social performance? J. Corp. Finance, 41(C), 591–609.

[7] Cassely, L., Larbi, S., Revelli, C., Lacroux, A., 2021. Corporate social performance (CSP) in times of economic crisis. Sustainability Accounting, Management and Policy Journal, 12(5), 913–942.

[8] Chen, H., Chiang, R. H. L., & Storey, V. C., 2012. Business intelligence and analytics: From big data to big impact. MIS Quarterly, 36(4), 1165-1188.

[9] Chevrollier, N., Zhang, J., Nijhof, A., 2019. The predictive value of strategic orientation for ESG performance over time. Corp. Govern., 20(1), 123–142.

[10] Crace, L., Gehman, J., 2022. What really explains ESG performance? Disentangling the asymmetrical drivers of the triple bottom line. Organ. Environ., 36(1), 150–178.

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

[12] Drempetic, S., Klein, C., Zwergel, B., 2020. The influence of firm size on the ESG score: corporate sustainability ratings under review. J. Bus. Ethics, 167(2), 333–360.

[13] Foo Nin, H., Hui-Ming Deanna, W., Scott, J.V., 2012. A global analysis of corporate social performance: the effects of cultural and geographic environments. J. Bus. Ethics, 107(4), 423–433.

[14] Friede, G., Busch, T., & Bassen, A., 2015. ESG and financial performance: Aggregated evidence from more than 2000 empirical studies. Journal of Sustainable Finance & Investment, 5(4), 210-233.

[15] Galbraith, J. R., 1974. Organization design: An information processing view. Interfaces, 4(3), 28–36.

[16] Garcia, A., Mendes-Da-Silva, W., Orsato, R., 2017. Sensitive industries produce better ESG performance: evidence from emerging markets. J. Clean. Prod., 150(1137), 135–147.

[17] Garcia-Blandon, J., Argilés-Bosch, J.M., Ravenda, D., 2019. Exploring the relationship between CEO characteristics and performance. J. Bus. Econ. Manag., 20(6), 1064–1082.

[18] Jang, G.-Y., Kang, H.-G., Kim, W., 2022. Corporate executives' incentives and ESG performance. Finance Res. Lett., 49.

[19] Kotler, P., & Lee, N., 2006. Corporate social responsibility: Doing the most good for your company and your cause. Wiley.

[20] Maniora, J., 2015. Is integrated reporting really the superior mechanism for the integration of ethics into the core business model? An empirical analysis. J. Bus. Ethics, 140, 755–786.

[21] Martiny, A., Taglialatela, J., Testa, F., & Iraldo, F., 2024. Determinants of environmental social and governance (ESG) performance: A systematic literature review. Journal of Cleaner Production, 456, 142213.

[22] May, R. L., 1993. COSO - internal control: Committee of sponsoring organizations of the treadway commission. Management Accounting, 74(9), 60.

[23] Mervelskemper, L., Streit, D., 2017. Enhancing market valuation of ESG performance: is integrated reporting keeping its promise? Bus. Strat. Environ., 26(4), 536–549.

[24] Mooneeapen, O., Abhayawansa, S., Mamode Khan, N., 2022. The influence of the country governance environment on corporate environmental, social and governance (ESG) performance. Sustainability Accounting, Management and Policy Journal, 13(4), 953–985.

[25] Short, J.C., McKenny, A.F., Ketchen, D.J., Snow, C.C., Hult, G.T., 2015. An empirical examination of firm, industry, and temporal effects on corporate social performance. Bus. Soc., 55(8).

[26] [25] Shu, H., Tan, W., 2023. Does carbon control policy risk affect corporate ESG performance? Econ. Modell., 120.

[27] Teece, D. J., 1986. Profiting from Technological Innovation: Implications for Integration, Collaboration, Licensing and Public Policy. Research Policy, 15(6), 285–305.

[28] Teece, D. J., Pisano, G., & Shuen, A., 1997. Dynamic capabilities and strategic management. Strategic Management Journal, 18(7), 509-533.

[29] Tornatzky, L. G., & Fleischer, M., 1990. The Processes of Technological Innovation. Lexington Books.

[30] Umar, Z., Kenourgios, D., Papathanasiou, S., 2020. The static and dynamic connectedness of environmental, social, and governance investments: international evidence. Econ. Modell., 93, 112–124.

[31] Waller, M. A., & Fawcett, S. E., 2013. Data science, predictive analytics, and big data: A revolution that will transform supply chain design and management. Journal of Business Logistics, 34(2), 77-84.

[32] Wang, L., Le, Q., Peng, M., Zeng, H., Kong, L., 2022. Does central environmental protection inspection improve corporate environmental, social, and governance performance? Evidence from China. Bus. Strat. Environ., 1–23.

[33] Yan, Y., Cheng, Q., Huang, M., Lin, Q., Lin, W., 2023. Government environmental regulation and corporate ESG performance: evidence from natural resource accountability audits in China. Int. J. Environ. Res. Publ. Health, 20(1).

[34] Che Xiaoli & Hu Qingyu. (2024). A Brief Discussion on the Impact of Artificial Intelligence (AI) on the ESG Ratings of Listed Companies. Commercial Exhibition Economy (15), 138-141.

[35] Dai Zhixiang. (2024). Supplier Management Strategies Under Supply Chain Digital Transformation. Market Modernization (20), 60-62.

[36] Gao Linyan. (2025). Research on Innovative Strategies for Corporate Financial Management Based on Artificial Intelligence. Bohai Economic Outlook (01), 95-97.

[37] Han Yonggang. (2024). Application of Artificial Intelligence in Supply Chain Management. China Logistics and Purchasing (14), 101-102.

[38] Huang Dong. (2024). ESG Investment Combined with AI Technology. China Finance (17), 56-58.

[39] Lu Yue, Ma Minghui, Chen Yongchang & Zhang Haotian. (2023). Empowering Green Development with Artificial Intelligence. China Population, Resources and Environment (10), 100-111.

[40] Sun Bei. (2023). Analysis of Operational Capability of Listed Companies: A Case Study of Midea Group. Accountant (18), 25-28.

[41] Sun Wenyuan & Liu Yushan. (2023). Research on the Mechanism of Artificial Intelligence's Impact on the Labor Market. East China Economic Management (03), 1-9.

[42] Tong Jian. (2024). Research on the Impact of Artificial Intelligence Technology Applications on Financial Industry ESG Performance (Master’s Thesis, Anhui University of Finance and Economics). Master’s

[43] Wu Fei & Xu Siyang. (2022). Application of Artificial Intelligence Technology and Market Value of Listed Companies. Modern Economic Exploration (11), 77-92.

[44] Xu Jiayun, Shen Hanyu & Zhou Xinbo. (2024). Development of Artificial Intelligence and Corporate ESG Performance. World Economy Research (09), 120-134+137.

[45] Xu Xiaodan & Hui Ning. (2024). Research on the Impact of Artificial Intelligence on the Green and Low-Carbon Development of Industry. Journal of Shaanxi Normal University (Philosophy and Social Science Edition) (06), 74-86.

[46] Yao Jiaquan, Zhang Kunpeng, Guo Lipeng & Feng Xu. (2024). How Can Artificial Intelligence Enhance Corporate Production Efficiency? — From the Perspective of Adjusting Labor Skill Structure. Management World (02), 101-116+133+117-122.

[47] Zhang Wei. (2025). Research on the Impact of Artificial Intelligence on Audit Work. Time-Honored Brand Marketing (02), 52-54.

[48] Zhang Xuan, Li Zijian, Li Chuntao. (2019). Banking Competition, Financing Constraints, and Corporate Innovation: Empirical Evidence from Chinese Industrial Enterprises. Financial Research (10), 98-116.

[49] Zhong Juan, Ding Yifan, Lin Zi'ang & Wei Yanjie. Application of Artificial Intelligence and Corporate Customer Diversification: A Quasi-Natural Experiment Based on AI Innovative Application Pilot Areas. Foreign Economy and Management, 1-20.

[50] Zhu Li & Jiang Wenqi. (2024). Artificial Intelligence, ESG Performance, and Corporate Green Governance Level. Technology Economics and Management Research (12), 71-76.

[51] Zhu Siwei, Liang Ran & Lu Kangjuan. (2024). The Impact of Artificial Intelligence and Corporate Digital Responsibility on Corporate Social Performance: Evidence Based on the ESG Performance of Chinese Listed Companies. Journal of Xi'an University of Finance and Economics (06), 64-79.