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The Impact of AI Application on Corporate ESG Performance: Empirical Evidence from Shanghai and Shenzhen A-share Listed Enterprises

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Abstract:

In the context of the digital economy and sustainable development, artificial intelligence (AI) has emerged as an important technological approach for enterprises to enhance ESG governance. Using Shanghai and Shenzhen A-share listed enterprises from 2010 to 2024 as the research sample, this study empirically examines the impact of AI application on corporate ESG performance. The results show that AI application significantly improves corporate ESG performance, with stronger effects observed among state-owned enterprises and large enterprises. These findings remain robust after excluding high-tech enterprises and shortening the sample period. This study extends the literature on the economic consequences of AI by shifting attention from financial outcomes to non-financial ESG performance and provides empirical evidence for enterprises to develop differentiated AI-enabled ESG strategies.

Keywords: AI Applications; ESG Performance; Corporate Sustainability; Heterogeneity Analysis

1 Introduction

As global climate governance and sustainability regulation become increasingly stringent, the European Union's Corporate Sustainability Reporting Directive (2022) (CSRD) mandates domestic and overseas listed enterprises to fully disclose ESG information, and ESG performance has become an important strategic factor influencing market access, financing costs, and long-term competitiveness. For domestic enterprises, improving ESG is not only a passive option to tackle external regulatory constraints, but also an inherent demand for green transformation and high-quality development. However, listed enterprises in China put "emphasis on disclosure over substance", and sustainable governance is difficult to land due to technical shortcomings (Garel & Petit-Romec, 2021). Since 2016, China has continuously introduced AI support policies to provide institutional support for the intelligent transformation of enterprises. Against this background, AI, as a new-generation digital technology with autonomous learning and full-process data governance capabilities, provides a new pathway for addressing challenges in corporate ESG practices.

Based on existing empirical evidence, previous literature has primarily examined the financial value of AI. In the dimension of the capital market, numerous studies have confirmed that AI R&D and implementation can raise the long-term valuation of enterprises and promote the excess return of stocks, but short-term high technology investment will suppress the short-term expectations of the market (Eisfeldt et al., 2023). In the aspect of corporate internal operation, studies have documented that AI can reshape the human resources structure and organizational structure of enterprises, and the popularization of AI can promote the streamlining of management and the reform of organizational flattening (Huang et al., 2026). To sum up, the existing research on AI basically conducts in-depth discussions around four financial and operational themes: corporate value (Eisfeldt et al., 2023), stock return (Eisfeldt et al., 2023), employee structure (Huang et al., 2026), and internal organizational structure. Little studies have systematically examined the mechanisms through which AI affects the three non-financial dimensions of ESG: environment, social responsibility, and corporate governance.

Using China's A-share listed enterprises in China from 2010 to 2024 as research samples, this paper examine the relationship between AI application and ESG performance. Empirically, this paper uses Sino-Securities ESG rating data to measure corporate ESG performance, constructs corporate AI application indicators through text analysis, and empirically tests the baseline impact of AI on ESG performance. The research found that AI application can effectively enhance the comprehensive ESG performance of enterprises. Further research indicates that this positive empowerment effect is more prominent in the sample of state-owned enterprises and large enterprises. After completing a series of sensitivity tests, the above core conclusions remain valid.

The contributions of this study are threefold. First, this paper contributes to the research on the economic consequences of AI. Existing AI empirical literature focuses on financial outputs such as enterprise market capitalization, stock income, and personnel structure (Eisfeldt et al., 2023), which rarely focuses on ESG-related non-financial performance. This study expands existing AI research by extending the focus from financial outcomes to ESG-related non-financial performance. Second, this study provides an emerging explanatory perspective by identifying technological drivers of ESG performance. Existing studies mostly rely on traditional variables such as corporate governance and external supervision to explain the sustainable performance of enterprises. This paper provides evidence that AI can significantly promote the comprehensive ESG rating of listed enterprises, and identifies technological drivers of corporate ESG performance. Third, this paper advances the analysis of heterogeneous effects in technology-enabled ESG improvement. In the past, related studies paid more attention to static testing. This paper distinguishes the heterogeneity of property rights and scale, quantifies the sustainable gain of long-term intelligent investment, and makes up for the insufficient stratified testing in the existing literature.

The remaining sections are arranged as follows. Section 2 provides the existing literature and proposes research hypotheses. Section 3 introduces the research design. Section 4 reports the empirical results. Section 5 concludes.

2 Literature Review and Research Hypotheses

2.1 AI-Related Research

AI depends on machine learning and predictive algorithms to realize autonomous data analysis and dynamic decision-making (Wu et al., 2022). Within the digital technology system, AI has distinct differences from digital transformation and big data. Specifically, digital transformation focuses on the electronic transformation of all businesses, and big data only provides basic storage and computing power, while AI can facilitate the identification of operational and governance risks and support enterprises in developing long-term sustainability strategies (Yang et al., 2022). However, the existing empirical research often confuses these concepts, which makes it difficult to get rid of the interference caused by ordinary digital behavior.

Based on the economic consequences of AI application, the existing research has formed a relatively mature analysis paradigm. From the aspect of the capital market, the literature confirms that AI R&D and implementation can raise the long-term valuation of enterprises and improve the excess return of stocks, but high technology investment will suppress market expectations in the short term (Eisfeldt et al., 2023). From the aspect of corporate internal operation, the research continuously verifies the deep reshaping of human resource structure and organizational structure by AI (Huang et al., 2026). On the whole, almost all the existing research on the economic consequences of AI focuses on financial output indicators, and few studies systematically explore how AI affects three-dimensional non-financial indicators. of environment, society and corporate governance, thus leaving an important research gap.

2.2 ESG Related Studies

ESG comprehensively evaluates the sustainable development capability of enterprises through three-dimensional indicators of environment, social responsibility and corporate governance, and its core analysis framework is built

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by stakeholder theory and principal-agent theory. According to Freeman's (1984) stakeholder theory, enterprises need to take into account the demands of employees, governments, investors and other subjects. Meanwhile, ESG practices such as environmental governance, labor protection and transparent disclosure are crucial for enterprises to respond to the demands of multiple interests. The principal-agent theory proposed by Jensen & Meckling (1976) reveals that management has short-sighted motivations to cut long-term ESG investment, selective disclosure and even greenwashing, while the function of AI to leave traces and automatic verification in the whole process can restrict management's opportunistic behavior and alleviate agent conflicts (Di Vaio et al., 2024).

As for empirical research on ESG drivers, the existing literature mainly forms two branches. One is the perspective of internal governance, focusing on the impact of internal factors such as board characteristics, ownership structure, executive incentives, and internal control on the willingness of enterprises to invest in ESG (Cucari et al., 2018). The other is the perspective of external supervision, which examines the constraint effects of external forces such as institutional investors, analyst tracking, media supervision and industry supervision on the sustainable behavior of enterprises (Friede et al., 2015). However, existing studies ignore AI as an emerging technology driver, and only a few studies discuss the impact of digital transformation on ESG, failing to strip the differentiated path between AI and ordinary digital tools.

2.3 Hypotheses Development

From the perspective of technical logic, AI empowers ESG through three paths. From the environmental aspect, AI can realize real-time monitoring and risk warning of carbon emissions and energy consumption. From the social aspect, AI can strengthen supply chain compliance screening and employee rights protection. From the governance aspect, AI improves information transparency, consolidates internal control and optimizes decision-making efficiency. Li et al. (2025), based on the data of A-share listed enterprises, confirmed that AI can significantly improve the corporate ESG performance, mainly through two channels: promoting digital innovation and strengthening the quality of internal control.

H1: AI application can significantly improve the corporate ESG performance.

Based on the theory of corporate governance and institutional logic, state-owned enterprises have both profitability and policy objectives, and their executive performance appraisal contains ESG hard indicators (Spagnuolo et al., 2025). Institutional incentives also urge them to prioritize AI in ESG governance scenarios. Private enterprises focus on short-term profits, and AI investment mostly serves to increase production efficiency. Meanwhile, state-owned enterprises are more likely to obtain green subsidies and low-interest credit (Zhang, 2024), and the advantages of resource matching further amplify the governance efficiency of AI.

H2: Compared with non-state-owned enterprises, AI has a stronger promoting effect on ESG performance of state-owned enterprises.

Based on the resource-based theory (Barney, 1991), AI empowerment of ESG needs abundant capital, data and talent reserves as support (Dzhengiz & Niesten, 2020), so the promoting effect of AI on ESG is more pronounced in larger-scale enterprises. Large enterprises have both a resource base and higher stakeholder attention, capable of continuously investing in long-term projects such as carbon emission accounting and supply chain management and control. Small and medium-sized enterprises, on the other hand, are subject to financial constraints and a weak digital foundation, and AI investment focuses on improving production efficiency, making it difficult to balance long-term ESG governance.

H3: Compared with small and medium-sized enterprises, AI has a stronger promoting effect on the ESG performance of large enterprises.

3 Empirical Design

3.1 Sample Selection and Data Sources

This paper selects Shanghai and Shenzhen A-share listed enterprises from 2010 to 2024 as the initial research sample, with the sample period from 2010 to 2024. Financial data and corporate governance data are sourced from the CSMAR database, ESG rating data are obtained from the Sino-Securities ESG database, and AI-related data are obtained through textual analysis of corporate annual reports of listed enterprises.

According to the existing research, this paper processes the initial sample as follows: (1) excluding the financial industry sample; (2) excluding ST, *ST and PT listed enterprises samples; (3) excluding the sample of B-share listed enterprises; (4) excluding samples with missing values in main variables; (5) winsorize all continuous variables at 1% and 99% quantiles to control for the effects of extreme values. After the above screening, 46,940 "*firm-year*" observations were finally obtained.

3.2 Variable Definition

3.2.1 Explained Variables

ESG performance (ESG). Adopting the Sino-Securities ESG Rating Index, this paper draws on the popular processing methods of ESG empirical research, such as those of Ferrell et al. (2016), to make industry adjustments and obtains the industry-adjusted ESG score as the measurement index of corporate ESG performance. The higher the value, the better the corporate ESG performance.

3.2.2 Core Explanatory Variables

AI Application (AI). This paper constructs the word frequency index of AI based on the text mining of annual reports of listed enterprises. This index identifies and counts the frequency of AI-related terms by structured text analysis and keyword matching of enterprise annual reports, thus describing the depth and breadth of corporate AI application. Based on the popular processing method of Wu et al. (2022) and others, this paper transforms the original word frequency by adding 1 and then taking the natural logarithm.

3.2.3 Control Variables

To control for the impact of other potential variables on the research results,, this paper follows Ferrell et al., (2016) and selects the following corporate financial and governance characteristic variables that may affect ESG performance: enterprise size (Size), asset-liability ratio (Lev), return on assets (ROA), rate of operating revenue growth (Growth), board size (Board), independent director ratio (Indr), enterprise age (Age), shareholding ratio of the largest shareholder (First), nature of property right (SOE), and operating cash flow (Cash). The main variable definitions are shown in Table 1.

Table 1 Variable Definition

Name	Symbol	Measurement
ESG Performance	ESG	The value of Sino-Securities ESG rating score adjusted by industry average
AI Applications	AI	Add 1 to the word frequency of AI-related keywords in the annual report and take natural logarithm
Enterprise Size	Size	Natural Logarithm of Total Assets
Asset-liability Ratio	Lev	Total Liabilities/Total Assets
Return on Assets	ROA	Net Profit/Total Assets
Rate of Operating Revenue Growth	Growth	(Operating income for the current period − Operating income for the previous period) /Operating income for the previous period
Board Size	Board	Number of Directors
Independence of the Board	Indr	Number of Independent Directors/Board Size
Age of Listing	Age	Current Year − Year of Initial Listing +1
Equity Concentration	First	Ownership Ratio of the Largest Shareholder
Nature of Property Rights	SOE	1 for State-owned Enterprises and 0 for Non-state-owned Enterprises
Cash Flow Ratio	Cash	Net Cash Flows from Operating Activities/Total Assets

3.3 Model Setting

To examine the impact of AI application on corporate ESG performance, this paper constructs the regression model:

$$ESG_{i,t} = \alpha + \beta AI_{i,t} + \gamma Control_{i,t} + \mu_i + \lambda_t + \epsilon_{i,t}$$

In the formula, the subscript i means the enterprise, and the subscript t refers to the year, respectivly. $ESG_{i,t}$ is industry- adjusted corporate ESG scores; $AI_{i,t}$ is the degree of AI application of the enterprise. $Control_{i,t}$ is a series of control variables. μ_i is the fixed effect of enterprises, aiming to absorb the inherent characteristics of enterprises that do not change with time. λ_t is the fixed effect of the year, which captures the common impact of the macroeconomy, policy shocks and other annual macro-level factors; $\epsilon_{i,t}$ is a random perturbation term.

4 Empirical Analysis

4.1 Descriptive Statistics

Descriptive statistical results for the main variables are shown in Table 2. The whole sample has a total of 46,940 observations. The mean value of the explained variable ESG (industry-adjusted ESG score) is 68.62, the standard deviation is 8.75, and the range is 42.98~88.34. This suggests that ESG performance among A-share listed enterprises varies considerably, and the leading enterprises exhibit substantially higher sustainability performance than their lower-performing counterparts. The mean value of the core explanatory variable AI is only 0.31, with 0 as both the median and 75th quantile. Thus, most domestic

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listed enterprises have not yet deployed AI-related technologies on a large scale, and the overall digital transformation of the industry is low.

Table 2 Descriptive Statistical Scales

Variable	N	Mean	SD	Min	p25	p50	p75	Max
ESG	46940	68.6233	8.7509	42.9800	63.5200	68.7800	74.2600	88.3400
AI	46940	0.3109	0.6890	0.0000	0.0000	0.0000	0.0000	3.2581
Size	46940	22.2706	1.3209	19.9271	21.3282	22.0562	22.9942	26.4722
Lev	46940	0.4242	0.2077	0.0540	0.2575	0.4163	0.5782	0.9052
ROA	46940	0.0317	0.0637	-0.2484	0.0104	0.0337	0.0633	0.1918
Growth	46940	0.1424	0.3744	-0.5774	-0.0453	0.0885	0.2463	2.1843
Board	46940	8.4335	1.6451	5.0000	7.0000	9.0000	9.0000	14.0000
Indr	46940	0.4550	0.1579	0.0000	0.3333	0.4286	0.5556	1.0000
Age	46940	11.6622	7.9395	1.0000	5.0000	10.0000	18.0000	30.0000
First	46940	0.3354	0.1487	0.0813	0.2200	0.3112	0.4333	0.7418
SOE	46940	0.3326	0.4712	0.0000	0.0000	0.0000	1.0000	1.0000
Cash	46940	0.0452	0.0687	-0.1617	0.0071	0.0446	0.0850	0.2392

4.2 Baseline Regression Results and Analysis

Table 3 reports the baseline regression results of the impact of AI applications on corporate ESG performance. Column (1) is the OLS regression controlling only for industry and year fixed effects, with a coefficient of 0.7338 for AI, which is significantly positive at 1%. Column (2) has added all control variables, and the coefficient of AI is 0.5620, which is still significantly positive at 1%. Column (3) is the core model of this paper, that is, the two-way fixed effect model that controls both individual fixed effects and year fixed effects of enterprises simultaneously. The coefficient of AI is 0.3273, which is significantly positive at 1%. The above results prove that no matter what model setting is adopted, AI applications can significantly improve corporate ESG performance, and this paper assumes that H1 is verified.

Table 3 Baseline Regression Results

	(1) ESG	(2) ESG	(3) ESG
AI	0.7338***	0.5620***	0.3273***
	(12.38)	(10.32)	(3.86)
Size		2.4390***	2.3743***
		(62.53)	(16.84)
Lev		-8.2462***	-7.3879***
		(-34.94)	(-15.33)
ROA		15.8266***	3.1327***
		(20.91)	(3.64)
Growth		-0.9122***	-0.5969***
		(-8.35)	(-6.35)
Board		-0.1247***	-0.1139**
		(-4.84)	(-2.05)
Indr		0.1447	-0.6074***
		(0.58)	(-3.00)
Age		-0.2417***	-0.4326*

	(1) ESG	(2) ESG	(3) ESG
		(-41.90)	(-1.68)
First		-0.5968**	3.0611***
		(-2.22)	(3.50)
SOE		1.4486***	0.5265
		(14.63)	(1.51)
Cash		-0.0514	-2.3421***
		(-0.08)	(-3.72)
Constant	64.3964***	18.2292***	22.0208***
	(158.26)	(21.37)	(6.97)
Year	Yes	Yes	Yes
Industry	Yes	Yes	Yes
Firm Effect	No	No	Yes
N	46940	46940	46940
r^2_a	0.0733	0.2153	0.0914
F	104.2450	281.1745	65.3316

Note: t values in parentheses; * p <0.1, ** p <0.05, *** p <0.01.

4.3 Heterogeneity Analysis

4.3.1 Heterogeneity of Property Rights

To test H2, we divide the sample into state-owned enterprises and non-state-owned enterprises based on property rights. Regression results of the two groups are shown in Table 4. In the state-owned enterprise samples in Column (1), the coefficient of AI is 0.9172, which is significant at 1%. In the non-state-owned enterprise samples in Column (2), the coefficient of AI is 0.4681, which is also significant at 1%, but the coefficient value is about half that of state-owned enterprises. The coefficient difference test between groups (Chow test) indicates that there are statistically significant differences in the coefficients between the two groups. This result supports the theoretical expectation in this paper that state-owned enterprises can more effectively translate AI into ESG performance by virtue of their institutional incentives, resource matching capabilities and policy implementation advantages.

4.3.2 Enterprise Size Heterogeneity

To test H3, this paper takes the median of enterprise size as the grouping basis, and divides the sample into two groups: large enterprises and small and medium-sized enterprises. Table 4 reports the regression results for the two groups. In the large enterprise samples in Column (3), the coefficient of AI is 1.0221, which is significant at 1%. In the sample of small and medium-sized enterprises in Column (4), the coefficient of AI is 0.2312, which is also significant at 1%, but the coefficient value is only 22.6% of that of large enterprises. The difference in coefficients between groups is significant, which verifies H3 in this paper. Thus, the ESG dividend of AI has scale bias, and large enterprises can more fully release the empowering effect of AI in sustainable development by virtue of their resource capability and governance willingness.

Table 4 Regression Results of Property Rights Heterogeneity

	(1) SOE ESG	(2) Non-SOE ESG	(3) Big ESG	(4) Small ESG
AI	0.9172***	0.4681***	1.0221***	0.2312***
	(7.59)	(7.71)	(12.15)	(3.29)
Size	2.6511***	2.3600***	2.7577***	2.0038***
	(43.85)	(44.98)	(40.81)	(23.04)
Lev	-8.9198***	-7.7758***	-8.8001***	-7.4562***
	(-20.89)	(-27.38)	(-21.73)	(-25.21)

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	(1) SOE ESG	(2) Non-SOE ESG	(3) Big ESG	(4) Small ESG
ROA	14.8102***	15.5102***	20.2834***	13.2626***
	(9.78)	(17.77)	(14.45)	(14.84)
Growth	-0.9849***	-0.8180***	-1.1600***	-0.6274***
	(-4.94)	(-6.29)	(-6.97)	(-4.40)
Board	-0.1067**	-0.1072***	-0.1370***	-0.1249***
	(-2.55)	(-3.28)	(-3.67)	(-3.59)
Indr	1.0642**	-0.2425	0.8068**	-0.4846
	(2.28)	(-0.82)	(2.02)	(-1.53)
Age	-0.1361***	-0.2849***	-0.1713***	-0.2952***
	(-14.68)	(-38.30)	(-20.15)	(-37.05)
First	-1.6639***	-0.5961*	-2.0799***	-0.0065
	(-3.61)	(-1.80)	(-5.27)	(-0.02)
Cash	0.4442	-0.0188	1.5181***	1.4036***
	(0.41)	(-0.03)	(10.83)	(10.05)
Constant	13.0167***	21.1795***	0.5353	-0.2996
	(10.42)	(17.58)	(0.54)	(-0.39)
Controls	Yes	Yes	11.3179***	27.6464***
Year	Yes	Yes	(6.98)	(14.78)
Industry	Yes	Yes	Yes	Yes
N	15614	31326	Yes	Yes
r^2_a	0.2518	0.2133	Yes	Yes

Note: * p <0.1, ** p <0.05, *** p <0.01.

4.4 Robustness Test

4.4.1 Excluding Samples of High-tech Enterprises

Considering that high-tech enterprises have strong technological innovation attributes, their ESG performance may be driven by various technical factors, rather than AI application alone. This paper excludes the sample of high-tech enterprises and re-regresses, with the results shown in Table 5. After excluding high-tech enterprises, the coefficients of AI are 0.3096, 0.2842 and 0.1700 in Columns (1)–(3), respectively, all of which remain significantly positive (at least significant at 10%), consistent with the baseline regression results. This indicates that the promoting effect of AI application on ESG is not driven by the specific characteristics of high-tech enterprise samples, and the conclusion has good sample robustness.

4.4.2 Shortening the Sample Period

Around 2016 is a vital watershed for AI development. Before that, the frequency of AI-related words in the annual reports of sample enterprises is extremely low, the proportion of zero values is high, and the insufficient variation of core explanatory variables may affect the estimation efficiency. To ensure that the study conclusions are not affected by the earlier sample distribution, this paper limits the sample period to 2016-2023 for re-regression, with the results shown in Table 5. After shortening the sample period, the coefficients of AI are 0.7293, 0.5573 and 0.1423 in Columns (4)–(6), respectively, all of which are significantly positive, consistent with the baseline regression conclusion, and the conclusions in this paper are robust in the time dimension.

Table 5 Robustness Test Regression Results

	(1) ESG	(2) ESG	(3) ESG	(4) ESG	(5) ESG	(6) ESG
AI	0.3096***	0.2842***	0.1700*	0.7293***	0.5573***	0.1423*
	(4.38)	(4.33)	(1.65)	(11.81)	(9.88)	(1.67)

	(1) ESG	(2) ESG	(3) ESG	(4) ESG	(5) ESG	(6) ESG
Size		2.1464***	2.3726***		2.4254***	2.7456***
		(32.21)	(11.93)		(56.07)	(14.09)
Lev		-8.0375***	-8.2148***		-8.9550***	-8.1029***
		(-23.51)	(-11.86)		(-33.82)	(-12.98)
ROA		17.3887***	3.8985***		13.6052***	-0.9144
		(16.12)	(3.27)		(16.61)	(-1.00)
Growth		-0.9153***	-0.6168***		-0.8787***	-0.5379***
		(-5.63)	(-4.33)		(-6.94)	(-4.98)
Board		-0.0082	-0.1047		-0.1179***	-0.1224*
		(-0.22)	(-1.31)		(-4.00)	(-1.92)
Indr		-0.1313	-0.9038***		-0.0434	-0.8069***
		(-0.39)	(-3.31)		(-0.16)	(-3.67)
Age		-0.1578***	-1.1723*		-0.2265***	-0.4713**
		(-14.74)	(-1.72)		(-36.43)	(-2.14)
First		-0.0115	3.9554***		-0.4548	0.6064
		(-0.03)	(2.97)		(-1.48)	(0.50)
SOE		0.7249***	0.5007		1.3541***	0.7381*
		(4.66)	(0.93)		(11.75)	(1.74)
Cash		0.3992	-2.8523***		0.9522	-0.9291
		(0.45)	(-3.20)		(1.34)	(-1.31)
Constant	62.7260***	21.6612***	20.9710***	64.0193***	17.7272***	15.7928***
	(77.71)	(14.10)	(4.62)	(129.61)	(17.72)	(3.51)
Year	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes
N	23210	23210	23210	33910	33910	33910
r^2_a	0.0521	0.1524	0.0918	0.0785	0.2297	0.1028

Note: t values in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

5 Conclusions and Suggestions

Selecting Shanghai and Shenzhen A-share listed enterprises from 2010 to 2024 as the research sample, this paper uses the industry-adjusted Sino-Securities ESG score to measure the sustainable development of enterprises, and examines their internal relationship through progressive baseline regression, sub-sample heterogeneity test and multi-scheme robustness test.The multi-level baseline regression results consistently indicate that AI application significantly improves corporate ESG performance. According to further research, The property-right heterogeneity analysis further indicates that the promoting effect of AI on ESG is significantly stronger among state-owned enterprises than among non-state-owned enterprises. There are also significant differences in the regression coefficients between the two groups. The scale heterogeneity regression results in the two groups demonstrate that AI-empowered ESG has significant scale stratification, and the promoting effect of large enterprises is much higher than that of small and medium-sized enterprises. In multiple robustness tests, it is found that after excluding high-tech enterprises and shortening the sample observation interval, the positive promotion relationship of AI to corporate ESG performance is still established, and the findings are not driven by specific samples or time periods, which verifies the stability and universality of the baseline conclusions.

Based on the above empirical conclusions, AI is effective in improving the corporate ESG development, but its empowerment effect is restricted by property rights attributes and resource scale. Various types of enterprises present

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significant differentiation characteristics. To fully release the empowering value of AI in sustainable development, this paper puts forward suggestions from both enterprise and government aspects. From the aspect of the enterprise, a medium-and long-term intelligent transformation plan should be formulated, and key scenarios such as intelligent monitoring of carbon emissions, digital internal control and verification of supply chain social responsibility should be implemented in stages. It is also necessary to implement a differentiated transformation path. Specifically, state-owned enterprises and large enterprises rely on their capital and talent advantages to deploy green AI research and development, and build an integrated ESG digital management platform; private enterprises give priority to lightweight digital tools; SMEs are transformed step by step with the help of standardized common modules. From the aspect of government and regulatory authorities, layered supporting policies should be introduced for the transformation and differentiation of enterprises. First, it is crucial to implement differentiated support to provide special subsidies for digital transformation, tax reduction and low-interest technology loans for small and medium-sized enterprises. ESG mandatory disclosure rules and added disclosure requirements should be implemented for green AI applications. It is also of significance to adjust the assessment system of state-owned enterprises, and increase the assessment weight of green digitalization investment and ESG performance. Secondly, it is required to build a public digital sharing platform for the industry, open it to small and medium-sized enterprises and private enterprises at a low price, and reduce the cost of enterprises developing AI systems independently. Thirdly, a long-term incentive mechanism should be established to include enterprises' continuous investment in green AI as a bonus in ESG ratings, guide enterprises to adhere to long-term transformation, and promote the synergistic improvement of ESG in the whole market.

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