

Article

The Impact of Artificial Intelligence Application on Corporate ESG Performance: Evidence from Chinese A-Share Listed Firms

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Abstract

The application of artificial intelligence (AI) and the improvement of environmental, social, and governance (ESG) performance have become important concerns for contemporary firms. Understanding whether AI can be effectively integrated into corporate ESG practices has significant implications for sustainable development. Using panel data from Chinese A-share listed firms from 2009 to 2025, this study empirically examines the effect of AI application on corporate ESG performance through a fixed-effects model. The results show that AI application significantly improves corporate ESG performance, indicating that firms with higher levels of AI adoption tend to achieve better ESG outcomes. The heterogeneity analysis further reveals that this effect varies according to firms' technological intensity, industry pollution characteristics, and the strength of regional environmental regulation. Specifically, the positive effect of AI application is more pronounced among firms with lower technological intensity, firms operating in non-heavily polluting industries, and firms located in regions with stricter environmental regulation. The mediation analysis shows that AI application enhances ESG performance by promoting human capital upgrading and green technological innovation, thereby strengthening firms' internal capabilities and technological foundations for sustainable development. This study contributes to the literature by integrating AI application and ESG-oriented sustainable development within a unified analytical framework.

Keywords: artificial intelligence; ESG performance; green innovation; technology intensity; environmental regulation

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1. Introduction

China is currently experiencing a new wave of technological advancement, industrial transformation, and green economic and social development [1]. Emerging technologies, particularly artificial intelligence (AI), have become increasingly integrated into a wide range of industries. AI is now an important driver of economic growth, industrial upgrading, operational efficiency, and service optimization. However, as AI continues to transform production processes and everyday life, an important question arises: can firms maintain high environmental, social, and governance (ESG) standards while pursuing AI

innovation and expanding the application of AI technologies? ESG represents a sustainable development framework that emphasizes environmental responsibility, social responsibility, and corporate governance. Its objective is to promote corporate value creation while safeguarding broader public interests [2]. Because ESG principles are closely aligned with China's green development strategy, ESG investment and corporate ESG practices have attracted growing attention from firms, investors, regulators, and other stakeholders. As of September 2023, the number of signatories to the Principles for Responsible Investment had reached 5330 worldwide, including 142 organizations in mainland China, reflecting the continued expansion of ESG investment. By December 2023, 34.5% of Chinese A-share listed firms had published ESG-related reports, indicating a steady increase in corporate ESG disclosure. Investors, consumers, and regulators are also placing greater emphasis on corporate ESG performance and increasingly view it as an important indicator of firms' long-term value and risk exposure [3]. Therefore, integrating AI application with ESG performance improvement is not only a natural consequence of technological development but also an important pathway through which firms can achieve sustainable development.

Existing studies have extensively examined the determinants of corporate ESG performance from the perspectives of legitimacy theory, principal-agent theory, and related theoretical frameworks. These studies have focused on factors such as firms' financial characteristics, market environments, ownership structures, and stakeholder pressures. Some scholars argue that corporate ESG disclosure may be largely symbolic and intended to satisfy stakeholder expectations [4]. Accordingly, regional environmental regulation, investor preferences, and sociocultural conditions have been identified as important drivers of corporate ESG performance [5–8]. Within the literature on digitalization and intelligent technologies, recent studies have primarily investigated how the development of the digital economy and digital transformation affects corporate social responsibility and environmental performance. Most of these studies confirm that digitalization and digital transformation contribute positively to corporate ESG performance [9,10]. However, relatively few studies have examined the specific relationship between AI application and corporate ESG performance. From a theoretical perspective, AI possesses strong capabilities in data analysis, pattern recognition, and optimization and has become increasingly embedded in firms' design, production, and operational activities. This integration provides firms with enhanced opportunities for information collection and processing. On the one hand, AI enables firms to identify and manage environmental risks more accurately, improve the allocation of production factors, and increase capital efficiency [11]. On the other hand, the integration of AI into operational and management systems allows firms to understand employee needs more promptly and comprehensively and to disclose corporate governance information more transparently. These improvements can strengthen investor confidence, reduce operational risks, and ultimately contribute to better corporate ESG performance.

However, the relationship between AI application and corporate ESG performance may not be uniformly positive. Some studies argue that implementing ESG practices increases corporate costs, reduces profit margins, and may constrain firm growth [12]. Because environmental and social investments have not traditionally been regarded as essential expenditures, firms may face difficult trade-offs when they are required to make substantial long-term investments in both AI technologies and ESG-related activities. Although AI can improve resource efficiency in various ways, its development and operation are also associated with high energy consumption and carbon emissions. The rapid expansion of AI has therefore raised concerns about growing energy demand, particularly because the digital and information industries that support AI technologies are themselves highly energy-intensive. These concerns may be more pronounced in developing

countries, where insufficient human capital and industrial infrastructure can limit the benefits of intelligent industrial transformation. Although such transformation may increase production scale and efficiency, it may also generate adverse consequences, including unemployment, environmental pollution, and occupational injuries [13,14]. These outcomes are inconsistent with firms' efforts to improve ESG performance. In addition, the rules, policies, and regulatory frameworks governing the use of AI remain underdeveloped, creating risks related to data security, privacy, and ethical conduct [15]. AI application may strengthen firms' information advantages and improve their ability to identify changing stakeholder expectations. However, firms may also use these capabilities primarily to enhance ESG disclosure without making corresponding improvements in their substantive ESG practices. This could increase the risk of decoupling between ESG disclosure and actual corporate behavior [16], thereby weakening ESG performance. Existing research has paid insufficient attention to the overall effect of AI application on corporate ESG performance. It is therefore necessary to clarify whether a causal relationship exists between the two and to identify the theoretical mechanisms through which AI may influence ESG outcomes.

Accordingly, this study uses panel data from Chinese A-share listed firms covering the period from 2009 to 2025 to theoretically and empirically examine the effect of AI application on corporate ESG performance. It further investigates the mediating roles of human capital upgrading and green technological innovation in this relationship. In addition, the study examines whether the effect of AI application on ESG performance varies across firms with different levels of technological intensity, across industries with different pollution characteristics, and across regions with different levels of environmental regulation.

2. Literature Review and Research Hypotheses

2.1. Literature Review

Existing studies have established a positive relationship between digital transformation and corporate ESG performance. Digital technologies can improve information transparency, reduce coordination costs, and strengthen communication between firms and stakeholders [9,10]. However, digitalization, digital transformation, and artificial intelligence represent different analytical concepts. Digitalization generally refers to the use of digital technologies to improve existing processes, whereas digital transformation involves broader changes in organizational structures, business models, and stakeholder relationships. AI is a specific technological capability within this broader transformation process. Its distinctive feature lies in its ability to learn from data, generate predictions, identify complex patterns, and adjust decisions in response to new information [17,18]. AI therefore differs from conventional digital systems that primarily support information storage, transmission, and process standardization. It can participate more directly in organizational analysis and decision-making, making its effects on corporate sustainability theoretically different from the general information and efficiency effects attributed to digital transformation.

Recent international research has increasingly examined how these capabilities reshape corporate management. AI applications have expanded from the automation of routine tasks to operational forecasting, risk assessment, organizational coordination, and strategic decision support [17,18]. The automation–augmentation perspective suggests that AI may substitute for human involvement in standardized tasks while complementing managerial judgment in decisions characterized by uncertainty and complexity [19]. Accordingly, the value of AI depends on how firms redesign work processes and allocate decision authority between algorithms and human managers [20]. The AI capability perspective further argues that firms must combine technological resources with employee

expertise and organizational coordination to translate AI investment into sustained performance benefits [21]. These arguments reveal several mechanisms through which AI may influence ESG outcomes. AI can improve the early identification of environmental and social risks, support the adaptive allocation of resources, and strengthen managerial responses to stakeholder concerns. It may also alter firms' demand for skills and facilitate knowledge recombination, thereby promoting human capital upgrading and green technological innovation. These mechanisms extend beyond the conventional argument that digital transformation improves ESG performance mainly by increasing efficiency and reducing information asymmetry.

The diffusion of AI has also stimulated research on AI ethics and governance. Existing studies show that AI may create risks related to biased decisions, privacy protection, limited explainability, and unclear responsibility [15]. Organizational AI governance therefore requires firms to establish clear decision rights and monitoring procedures so that AI systems remain consistent with organizational objectives and stakeholder interests [22]. Human oversight and algorithmic auditing are also necessary when automated decisions may affect employees, customers, or other stakeholders [23]. These issues are closely related to ESG performance because poorly governed AI may weaken employee protection, information transparency, and corporate accountability. AI should therefore be viewed not only as a managerial resource but also as an object of corporate governance.

A related stream of literature examines the contribution of AI to sustainable development. AI may improve environmental performance by supporting energy management, resource allocation, pollution monitoring, and green innovation [24,25]. It may also strengthen corporate sustainability by improving workplace safety, supply-chain supervision, and ESG-related decision-making. However, the sustainability effects of AI are not necessarily positive. The operation of AI systems may increase energy consumption, while the diffusion of automation may create employment pressure and deepen technological inequality [13,26]. AI application may also generate privacy and accountability risks [15]. In addition, firms may use AI to improve ESG disclosure without making corresponding changes in their substantive practices, thereby increasing the risk of ESG decoupling [16]. Recent research therefore emphasizes that the sustainability value of AI depends on complementary organizational capabilities and responsible governance rather than on technological adoption alone [21–23].

Despite these advances, several research gaps remain. First, studies on digital transformation often treat digital technologies as a broad category and therefore provide limited evidence on the distinct ESG implications of AI [9,10]. Second, studies on AI-related employment mainly examine labor substitution and skill demand [27], whereas research on AI and green innovation focuses primarily on innovation performance [24,25]. These two streams have rarely been integrated to explain how AI affects corporate ESG performance. Third, existing studies provide insufficient evidence on whether the ESG effect of AI varies across firms, industries, and regulatory environments. Finally, much of the AI governance literature remains conceptual and offers limited firm-level evidence on the sustainability consequences of AI application. To address these gaps, this study examines the effect of firm-level AI application on corporate ESG performance and further investigates the roles of human capital upgrading and green technological innovation. It also identifies the organizational, industrial, and institutional conditions under which the ESG effect of AI becomes stronger or weaker, thereby providing a more integrated understanding of whether, how, and under what conditions AI contributes to corporate sustainability.

These gaps motivate a mechanism-based examination of the relationship between AI application and corporate ESG performance. The first gap raises the need to identify whether AI has an ESG effect that is distinct from the general efficiency and information-transparency effects associated with digital transformation. This provides the basis for

examining the direct effect of AI application on ESG performance in H1. The second gap suggests that AI may affect ESG performance not only through immediate operational improvements, but also through changes in firms' internal capabilities. In particular, AI may reshape the composition and quality of human capital and facilitate green technological innovation, thereby providing the theoretical foundation for H2 and H3. The third and fourth gaps further imply that these effects may depend on firms' organizational characteristics, industrial conditions, and institutional environments, as well as on the quality of AI governance. Accordingly, the following sections develop the direct effect of AI on ESG performance and then examine the mediating roles of human capital upgrading and green technological innovation.

2.2. AI Technology and Firm ESG Performance

A review of the literature indicates that AI, together with modern communication technologies, big data, and other advanced technological systems, is increasingly integrated into core corporate activities, including procurement, production, and business management, thereby exerting multidimensional effects on corporate ESG performance.

First, AI technology can create new employment opportunities [27] and increase firms' demand for highly skilled workers and employee training [28]. These changes may promote internal knowledge spillovers, improve labor productivity, and strengthen corporate governance. At the same time, firms can fulfill their social responsibilities and improve the quality of public services by developing new AI-enabled application scenarios, such as smart cities and intelligent healthcare. Second, integrating AI and intelligent manufacturing technologies into production processes can improve process standardization and precision while reducing unnecessary resource losses and pollutant emissions. By enhancing productivity and resource-use efficiency, AI can support cleaner and more efficient production [29]. AI also has considerable potential for pollutant-emission monitoring and environmental risk detection, enabling firms to identify environmental problems more accurately and respond to them more effectively. These capabilities can strengthen firms' fulfillment of environmental and social responsibilities. Finally, at the corporate governance level, the integration of AI with internal information systems can promote the continuous improvement of organizational structures and resource allocation. AI's powerful data collection and analytical capabilities enable managers to monitor and report corporate activities more comprehensively and efficiently, thereby supporting internal organizational optimization and improving governance efficiency [30]. In addition, AI generates technological spillover effects that help firms analyze and predict operational risks and changes in market demand, improve risk management, accelerate the creation and dissemination of new ideas, and enhance their ability to respond to stakeholder needs [17]. Through these mechanisms, firms can assess their ESG performance more accurately, identify problems promptly, and implement appropriate corrective measures.

In conclusion, AI application is expected to improve corporate ESG performance. By adopting AI technologies, firms can more effectively fulfill their social responsibilities, enhance ESG outcomes, and establish a stronger foundation for sustainable development. Accordingly, the following hypothesis is proposed:

H1: *AI technology can effectively improve the level of firm ESG performance.*

2.3. The Mediation Effect of AI on ESG Performance

2.3.1. Human Capital Upgrading Effect

With the widespread adoption of intelligent robots and highly automated control systems, AI is transforming production processes and replacing many repetitive, low-skilled jobs [29]. At the same time, because AI draws on knowledge from multiple disci-

plines, its diffusion has created a growing number of knowledge-intensive positions within firms [31]. Therefore, this study argues that AI can promote the upgrading of firms' human capital structure through both job substitution and job creation, thereby improving corporate ESG performance.

Specifically, the rapid development of AI has accelerated the upgrading and iterative improvement of automated equipment. As machines increasingly replace low-skilled workers in repetitive tasks, firms' demand for such labor has declined significantly [27]. At the same time, AI's strong data-processing and predictive capabilities enable firms to analyze consumer purchasing behavior and preferences more accurately, thereby partially substituting for traditional market analysts and sales personnel [32]. Consequently, the adoption of AI technologies may substantially reduce firms' demand for low-skilled labor. Compared with conventional technologies, AI is more versatile and adaptable, and its application scenarios continue to expand across different types and forms of work [33]. The ongoing development of AI has also created a growing number of highly skilled positions, including AI engineers and data analysts. These occupations typically require employees to possess specialized knowledge, advanced technical skills, and proficiency in AI-related technologies [34]. AI adoption therefore encourages firms to recruit more highly educated and skilled employees, provide existing workers with AI-related training, and attract additional technical and R&D personnel. Highly skilled employees are generally better able to understand and implement energy-saving and emission-reduction measures. They can also use AI technologies to improve productivity and reduce pollutant emissions, thereby contributing to better corporate ESG performance [35]. In addition, highly skilled employees tend to have stronger risk awareness and analytical capabilities, which can help firms identify and respond to potential risks and challenges and support stable operations and sustainable development [36].

In summary, this study argues that AI application can facilitate the optimization and upgrading of firms' human capital structure, thereby significantly improving corporate ESG performance. Accordingly, the following hypothesis is proposed:

H2: *AI application effectively improves the level of firm ESG performance by promoting human capital upgrading.*

2.3.2. Green Technology Innovation Effect

Technological progress is widely recognized as an important means of addressing environmental challenges. In particular, breakthroughs in green technologies and their broad application in energy, transportation, and manufacturing can support a more cost-effective transition to a low-carbon economy [37]. However, green innovation often requires substantial information, financial resources, and a strong technological foundation [38]. Consequently, information barriers, resource constraints, uncertain returns, and insufficient technological capabilities have become major obstacles to the advancement of green technologies. The integration of AI into green technology research and development offers a promising approach to overcoming these constraints.

First, AI can help reduce information asymmetry in the market. Firms can use AI to rapidly collect, integrate, and analyze information concerning consumers' demand for green products, technological developments, and their internal resources for green innovation, thereby improving the efficiency and quality of green innovation decisions [24]. Second, the integrative, collaborative, and generative capabilities of AI enable it to be applied across resource management, product development, and other corporate activities, continuously providing firms with new ideas and tools for innovation. AI also generates significant technological spillover effects. By accelerating the flow of information and knowledge within firms and across industrial chains, it can improve the efficiency of green

and low-carbon technological innovation [25]. Improved green technological innovation can reduce energy consumption, waste emissions, and pollutant generation, thereby mitigating firms' adverse environmental impacts. It can also enhance corporate reputation and establish firms as environmental leaders in the eyes of consumers and investors. These benefits may attract additional talent and resources, strengthen corporate competitiveness and sustainability, and ultimately improve ESG performance. Accordingly, the following hypothesis is proposed:

H3: *AI application effectively enhances the level of firm ESG performance by promoting green technology innovation.*

3. Results

3.1. Sample Selection

To test the research hypotheses, this study constructs the following fixed-effects models. Model (1) examines the direct effect of AI application on corporate ESG performance, whereas Models (2) and (3) assess the mediating roles of human capital upgrading and green technological innovation, respectively.

$$ESG_{i,t} = b_0 + b_1 AI_{i,t} + b_2 \sum Control_i + \delta_z + \rho_{i,t} \quad (1)$$

$$Human_Capital_{i,t} = b_0 + b_1 AI_{i,t} + b_2 \sum Control_i + \delta_z + \rho_{i,t} \quad (2)$$

$$Green_Innovation_{i,t} = b_0 + b_1 AI_{i,t} + b_2 \sum Control_i + \delta_z + \rho_{i,t} \quad (3)$$

where $AI_{i,t}$ and $ESG_{i,t}$ indicate the level of AI technology application and ESG performance of firm i in year t , respectively; $Human_Capital_{i,t}$ and $Green_Innovation_{i,t}$ represent the upgrading of human capital and the R&D status of green innovation, respectively.

3.2. Variable Selection

Artificial Intelligence (explanatory variable). This study uses firm-level artificial intelligence investment amount to measure the level of AI application. Compared with the density of industrial robots, AI investment amount provides a more direct and precise measure of firms' actual AI application. Industrial robots mainly capture the degree of automation in production processes, especially the substitution of machines for manual labor in manufacturing activities. Although industrial robot density can partly reflect intelligent manufacturing, it cannot fully capture the broader application of AI technologies in firms' production, operation, management, environmental monitoring, risk prediction, decision support, and governance optimization. Therefore, using industrial robot density may underestimate AI application in non-manufacturing firms and may also fail to reflect AI applications beyond automated production.

By contrast, firm-level AI investment amount reflects the resources that firms actually allocate to AI-related technologies, systems, equipment, algorithms, software, data infrastructure, and intelligent application scenarios. It can better capture firms' strategic commitment to AI adoption and the extent to which AI is embedded in their business activities. Since this study focuses on the impact of AI application on ESG performance, the explanatory variable should reflect not only production automation but also AI-enabled environmental management, social responsibility management, information disclosure, risk control, and corporate governance improvement. Therefore, AI investment amount is more consistent with the research objective of this study and provides a more accurate proxy for firms' AI application level.

Firm ESG performance (explained variable). ESG performance refers to a firm's actual performance in environmental responsibility, social responsibility, and corporate governance. It is a multidimensional concept that reflects a firm's sustainability practices, stakeholder responsibility, environmental management, and governance quality. Since ESG performance itself is not directly observable in empirical research, existing studies commonly use ESG ratings or ESG scores issued by third-party rating agencies as observable proxies for firms' ESG performance [39]. Therefore, the ESG score used in this study should be understood as a quantitative proxy for firm ESG performance rather than ESG performance itself.

This study uses the Huazheng ESG Index to measure firms' ESG performance. The choice of this index is mainly based on the following considerations. First, the Huazheng ESG Index is specifically designed for China's capital market and is more closely aligned with the institutional environment, regulatory requirements, disclosure practices, and corporate governance characteristics of Chinese listed firms. Compared with international ESG rating systems, such as Bloomberg and MSCI, the Huazheng ESG Index better reflects China-specific policy priorities, domestic environmental regulation standards, and the disclosure practices of Chinese listed companies. Therefore, it is more suitable for examining ESG issues in the context of China's A-share listed companies [40].

Second, after incorporating the reviewer's suggestion, this study extends the sample period to cover China's A-share listed companies from 2009 to 2025. This longer observation window places higher requirements on the measurement of ESG performance. In a long-period panel setting, the ESG indicator should have sufficient firm-year coverage and maintain a relatively consistent evaluation standard over time; otherwise, missing observations or changes in rating criteria may affect the comparability of ESG scores across years. The Huazheng ESG Index is therefore selected because it provides relatively complete and continuous ESG rating information for Chinese A-share listed companies during the expanded sample period [41]. This allows the study to construct a more consistent panel dataset and to examine the relationship between AI application and ESG performance over a longer time horizon.

Third, the Huazheng ESG Index has been widely adopted in empirical studies on ESG issues in the Chinese market, which supports its applicability in research on Chinese listed firms [40]. The Huazheng ESG evaluation system assesses listed companies' ESG performance through a hierarchical rating framework and classifies firms into nine rating categories, namely AAA, AA, A, BBB, BB, B, CCC, CC, and C, in descending order. To facilitate quantitative analysis, this study assigns numerical values from 9 to 1 to these nine categories, with 9 corresponding to the highest rating, AAA, and 1 corresponding to the lowest rating, C. A higher value indicates better corporate ESG performance.

Human capital upgrading (mediating variable). Human capital upgrading is measured using two indicators: the number of employees with bachelor's degrees and the proportion of such employees in the firm's total workforce [42].

Green technological innovation (mediating variable). This study measures green technological innovation using the number of green patent applications [43]. Green patents are further classified into green invention patents and green utility model patents to examine their respective roles in the relationship between AI application and corporate ESG performance.

Control variables. To more accurately identify the effect of AI application on firm ESG performance, this study controls for variables that may affect both firms' AI adoption and ESG outcomes. The control variables are selected from three aspects: firm financial characteristics, firm governance characteristics, and regional economic development level.

First, this study controls for firm financial characteristics, including return on equity (ROE), Tobin's Q (Q), and leverage ratio (LEV). ROE is included to capture firms' profita-

bility. Firms with higher profitability usually have stronger internal financial capacity and more available resources to invest in environmental governance, social responsibility activities, employee welfare, and corporate governance improvement. Therefore, controlling for ROE helps reduce the estimation bias caused by differences in firms' profitability and resource endowment. Tobin's Q is used to measure firms' market valuation and growth opportunities. Firms with higher Tobin's Q are generally regarded as having stronger growth potential and may have greater incentives to improve ESG performance in order to attract investors, maintain market reputation, and reduce financing constraints. In addition, Tobin's Q may also be associated with firms' digital transformation capability and willingness to adopt AI technologies. Therefore, including Tobin's Q helps isolate the impact of AI application on ESG performance from the influence of market expectations and growth opportunities. LEV is controlled because firms with different debt levels may face different financing pressures and risk constraints, which may affect their ESG investment decisions.

Second, this study controls for firm governance characteristics, including board size and institutional shareholding. Board size may affect the efficiency of corporate decision-making and the firm's ability to supervise ESG-related strategies. Institutional shareholding reflects the external governance role of institutional investors, who may exert pressure on firms to improve information disclosure, environmental responsibility, and corporate governance quality.

Third, this study controls for the level of regional economic development. Specifically, the economic development level is measured by the per capita GDP of the prefecture-level city where the firm is located. Regional economic development may influence firms' access to digital infrastructure, human capital, financing resources, and environmental governance capacity, thereby affecting both AI application and ESG performance.

3.3. Data Description

Corporate ESG performance data are obtained from the Huazheng ESG rating database. Firm-level AI application is measured by corporate AI investment data obtained from the China Stock Market and Accounting Research (CSMAR) database. Specifically, this variable captures firms' investment in artificial intelligence-related activities as reported in the CSMAR database and is used to proxy the extent of firm-level AI application. To mitigate potential skewness and facilitate interpretation, the dependent variable of corporate ESG performance and the independent variable of corporate AI investment are transformed using the natural logarithm. Data on the mediating variables and control variables are also obtained from the CSMAR database.

4. Empirical Results and Analysis

4.1. Descriptive Statistics and Correlation Analysis

Before conducting the main regression analysis, this study performs descriptive statistical and correlation analyses. Table 1 reports the descriptive statistics and correlation coefficients for all variables. The correlation coefficients are all below 0.70, suggesting that multicollinearity is unlikely to pose a serious concern.

Table 1. Descriptive Statistics and Correlation Analysis.

Variables	Obs	Mean	S.D.	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) ESG	44,924	4.305	0.076	1.000							
(2) AI	44,924	16.803	2.122	0.177	1.000						
(3) ROE	44,924	0.034	0.345	0.084	0.009	1.000					
(4) Q	44,924	1.981	1.191	−0.086	−0.152	0.000	1.000				

(5) LEV	44,924	0.417	0.214	−0.076	0.282	−0.094	−0.260	1.000			
(6) Boardsize	44,924	8.497	1.803	0.083	0.197	0.013	−0.132	0.227	1.000		
(7) Institutional_share- holding	44,924	43.07	24.981	0.117	0.231	0.041	−0.067	0.231	0.268	1.000	
(8) PGDP	44,924	11.313	0.51	0.076	0.203	−0.002	−0.029	−0.071	−0.135	−0.099	1.000

4.2. Benchmark Regressions

Table 2 presents the benchmark regression results for the effect of AI application on corporate ESG performance. Column (1) reports the results of the fixed-effects model including only the control variables. Column (2) further includes AI application to examine its effect on ESG performance. The coefficient of AI application is positive and statistically significant ($\beta = 0.0031$, $p < 0.01$), indicating that a higher level of AI application is associated with better corporate ESG performance. Therefore, H1 is supported. This result suggests that AI can improve ESG-related decision-making through enhanced data analysis and predictive capabilities, thereby contributing to stronger corporate ESG performance.

Table 2. Benchmark regression test and robustness test results.

	(1)	(2)	(3)	(4)	(5)	(6)
	ESG	ESG	Re_ESG	ESG	ESG	ESG
AI		0.0031 *** (8.4699)	0.0079 *** (4.3683)	0.0035 *** (8.1071)		
L.AI					0.002 *** (0.000)	
DID						0.015 *** (0.003)
ROE	0.0035 ** (2.1591)	0.0032 ** (2.0971)	0.0121 *** (2.8930)		0.003 ** (0.001)	0.004 * (0.002)
Q	−0.0044 *** (−11.7554)	−0.0039 *** (−9.7037)	0.0005 (0.2898)		−0.003 *** (0.000)	−0.004 *** (0.001)
LEV	−0.0711 *** (−23.0007)	−0.0778 *** (−22.6393)	−0.0220 (−1.3615)		−0.073 *** (0.004)	−0.065 *** (0.005)
Boardsize	0.0001 (0.3370)	−0.0000 (−0.0810)	0.0023 * (1.7357)		0.000 (0.000)	0.000 (0.001)
Institutional_sharehold- ing	0.0003 *** (8.4824)	0.0002 *** (6.4821)	0.0008 *** (4.3735)		0.000 *** (0.000)	0.000 *** (0.000)
PGDP	0.0154 *** (4.6201)	0.0143 *** (3.9837)	−0.0569 *** (−3.5182)		0.018 *** (0.004)	0.015 ** (0.006)
L.AI						
L.ROE				0.0124 (1.1146)		
L.Q				−0.0014 *** (−3.1427)		
L.LEV				−0.0711 *** (−17.6472)		
L.Boardsize				−0.0001 (−0.3777)		
L.Institutional_sharehold- ing				0.0004 *** (8.9062)		
L.PGDP				0.0105 ***		

				(2.5826)		
Constant	4.1564 *** (110.077)	4.1218 *** (100.3368)	3.8804 *** (21.0188)	4.1436 *** (89.0552)	4.086 *** (0.047)	4.145 *** (0.068)
Observations	49,980	44,924	13,835	45,182	40,687	32,657
R-squared	0.4011	0.3999	0.8218	0.4007	0.478	0.397
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

4.3. Robustness Tests and the Endogeneity Problem

4.3.1. Robustness Test

First, corporate ESG performance is remeasured using Bloomberg ESG scores, and Model (1) is re-estimated with this alternative dependent variable. Column (3) of Table 2 reports the results. The coefficient of AI application remains positive and statistically significant at the 1% level, providing further support for the positive effect of AI application on corporate ESG performance.

Second, because information disclosed in listed firms' annual reports may be subject to a reporting lag, all control variables are lagged by one period to reduce potential estimation bias arising from timing differences. Column (4) of Table 2 presents the results of this lagged specification. The coefficient of AI application remains positive and statistically significant at the 1% level, further confirming the robustness of the benchmark findings.

Third, this study uses one-period lagged AI application to further address the potential reverse causality problem. In the benchmark regression, AI application and ESG performance are measured in the same period. Under this setting, the estimated relationship may be affected by reverse causality: firms with better ESG performance may have stronger financing capacity, better governance foundations, and greater external recognition, which may enable them to increase AI investment. In other words, the positive coefficient of AI application may partly reflect the effect of ESG performance on AI adoption, rather than only the effect of AI application on ESG performance.

To reduce this concern, this study replaces current AI application with one-period lagged AI investment in the regression model. This means that AI investment in period (t-1) is used to explain ESG performance in period (t). Compared with the contemporaneous regression, this specification makes the timing of the variables clearer. Since AI investment in the previous period has already occurred before current ESG performance is measured, current ESG performance cannot directly affect previous AI investment. Therefore, if lagged AI application still has a significantly positive effect on current ESG performance, it suggests that earlier AI application contributes to the subsequent improvement of ESG performance, rather than the result being mainly driven by firms with better ESG performance increasing AI investment in the same period. This specification can therefore help address the reverse causality concern.

As shown in column (5) of Table 2, the coefficient of one-period lagged AI application remains significantly positive. This indicates that prior AI investment continues to promote firms' subsequent ESG performance after considering the timing difference between AI application and ESG performance. Therefore, the positive relationship between AI application and ESG performance is less likely to be fully explained by reverse causality. This result further supports the robustness of the benchmark conclusion.

Fourth, this study further employs a propensity score matching-difference-in-differences (PSM-DID) approach to alleviate the concern of reverse causality. Firms with better ESG performance may have stronger financial resources, governance capabilities, and innovation foundations, making them more likely to increase AI investment. Therefore, the

positive relationship identified in the benchmark regression may partly reflect the effect of ESG performance on AI application.

The PSM-DID approach addresses this concern in two steps. First, propensity score matching identifies control firms with similar pre-treatment ESG performance, financial characteristics, governance conditions, regional economic development, and industry characteristics. This reduces the possibility that firms entering a high-intensity AI application state already had systematically better ESG foundations. Second, the DID estimation compares the change in ESG performance before and after high-intensity AI application with the corresponding change among matched control firms. This approach focuses on the relative change following AI application rather than the initial difference in ESG levels, thereby helping distinguish the effect of AI application from firms' pre-existing ESG advantages.

Because most firms in the sample make some AI-related investment, this study defines the treatment according to AI investment intensity. A firm enters the treatment group when its AI investment reaches the top quartile of the industry-year distribution and remains at this level in the following year, while firms that never enter this sustained high-intensity state constitute the control group. After matching, the absolute standardized biases of all covariates are below 10%, and the two groups exhibit substantial common support. As shown in column (6) of Table 2, the DID coefficient is 0.015 and is significant at the 1% level, indicating that ESG performance improves significantly after firms enter the high-intensity AI application state. This result further alleviates the concern that the benchmark findings are primarily driven by firms with better ESG performance being more likely to increase AI investment.

Fifth, the relatively large number of missing observations before 2014 may affect the reliability of the results. To address this concern, this study excludes observations prior to 2014 and re-estimates the model using the restricted sample. Column (1) of Table 3 reports the results. The coefficient of AI application remains positive and statistically significant at the 1% level, consistent with the benchmark findings and further confirming their robustness.

Finally, Beijing, Shanghai, Chongqing, and Tianjin are municipalities directly administered by the central government and have economic scales and firm characteristics that are more comparable to those of provinces. Firms located in these municipalities may therefore exhibit extreme values in certain indicators, which could influence the estimation results. To reduce this potential bias and assess the stability of the findings, this study excludes firms located in the four municipalities and re-estimates the model. Column (2) of Table 3 reports the results. The coefficient of AI application remains positive and statistically significant at the 1% level, further confirming the robustness of the benchmark findings.

Table 3. Robustness test results.

	(1)	(2)	(3)	(4)
	ESG	ESG	AI	ESG
AI	0.0040 *** (7.5573)	0.0030 *** (7.6090)		0.0683 * (1.8155)
AI_IV			0.0083 ** (0.0036)	
ROE	0.0034 * (1.7388)	0.0027 ** (1.9669)	0.075 (0.0484)	0.0034 (0.7673)
Q	−0.0028 *** (−5.8847)	−0.0041 *** (−8.9119)	−0.0743 *** (0.0086)	0.0014 (0.4866)
LEV	−0.0892 ***	−0.0791 ***	1.0489 ***	−0.1436 ***

	(−19.6727)	(−20.6007)	(0.0754)	(−3.6083)
Boardsize	−0.0001	−0.0001	0.0356 ***	−0.0023
	(−0.1181)	(−0.1504)	(0.0066)	(−1.5249)
Institutional_shareholding	0.0003 ***	0.0002 ***	0.0033 ***	−0.0000
	(5.4674)	(6.2788)	(0.0009)	(−0.0962)
PGDP	0.0215 ***	0.0145 ***	−0.0038	0.0131
	(4.2777)	(3.2580)	(0.0992)	(1.5065)
Constant	4.0217 ***	4.1201 ***		
	(69.5220)	(81.7971)		
Observations	36,783	35,957	26,622	26,622
R-squared	0.4224	0.3997		−0.9572
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

4.3.2. Endogeneity Issues

The benchmark regression results show that AI application has a significant impact on firms' ESG performance. However, there may still be reverse causality between the two. Specifically, firms with better ESG performance may have stronger reputational advantages, better financing conditions, and greater strategic incentives to invest in AI technologies, which may in turn promote the improvement of their AI application level. In addition, some unobservable factors, such as managerial capability, firms' strategic orientation, local digital policy support, or industry-level technological trends, may simultaneously affect both AI investment and ESG performance, leading to potential omitted-variable bias. To mitigate these endogeneity concerns, this study further employs an instrumental-variable approach.

This study draws on the research design of Du et al. (2024) [44] and selects the interaction term between provincial optical cable density and the average AI application level of other firms in the same city and industry as the instrumental variable for firm-level AI application. This instrumental variable satisfies the relevance requirement. On the one hand, optical cable density reflects the level of regional digital infrastructure. AI application relies on data transmission, computing access, and the mobilization of digital resources. Therefore, a higher level of optical cable density provides firms with better basic conditions for deploying AI technologies. On the other hand, the average AI application level of other firms in the same city and industry reflects the external technology diffusion environment, peer demonstration effect, and competitive pressure, which may influence a firm's own likelihood of adopting AI technologies.

Meanwhile, this instrumental variable also has a certain exogeneity basis. After controlling for firm fixed effects, year fixed effects, and firm-level financial and governance characteristics, regional optical cable infrastructure and the technology diffusion environment among peer firms do not directly determine an individual firm's ESG performance. Instead, their effects are expected to operate mainly through the firm's own AI application. Therefore, this instrumental variable can help mitigate potential endogeneity concerns in examining the relationship between AI application and corporate ESG performance.

This study employs a two-stage least squares (2SLS) estimation to address potential endogeneity concerns, and the results are reported in columns (3) and (4) of Table 3. The first-stage regression results, shown in column (3) of Table 3, indicate that the coefficient of the instrumental variable is 0.0083 and is significant at the 5% level, suggesting that the instrumental variable is positively correlated with firm-level AI application. The F statistic for the excluded instrument is 5.35, with a p -value of 0.0207, indicating that the instru-

mental variable has explanatory power for the endogenous variable. In addition, the Kleibergen–Paap rk LM statistic is 6.141, with a p -value of 0.0132, rejecting the null hypothesis of underidentification. These results support the relevance of the selected instrumental variable. However, the Kleibergen–Paap rk Wald F statistic is 5.349, which is below the conventional threshold of 10, indicating a potential weak-instrument concern. Therefore, the conventional 2SLS estimates and associated statistical inference should be interpreted with caution.

The second-stage estimation results, shown in column (4) of Table 3, indicate that after using the instrumental variable to mitigate potential reverse causality and omitted-variable bias, the coefficient of AI application is 0.0683 and is significant at the 10% level. This suggests that AI application continues to have a positive effect on firms' ESG performance after accounting for potential endogeneity. Considering that the Kleibergen–Paap rk Wald F statistic is 5.349, this study further reports weak-instrument-robust inference results. The Anderson–Rubin Wald test rejects the null hypothesis that the coefficient of the endogenous variable is equal to zero, with a F statistic of 7.05 and a p -value of 0.0079. The Anderson–Rubin Wald chi-square test and the Stock–Wright LM test are also significant, with p -values of 0.0043 and 0.0046, respectively. These results provide additional support for the positive effect of AI application on corporate ESG performance. Accordingly, although the relatively low Kleibergen–Paap rk Wald F statistic remains a limitation of the instrumental-variable analysis, the weak-instrument-robust test results provide supportive evidence that the positive association between AI application and corporate ESG performance is not solely driven by reverse causality or omitted-variable bias. Overall, the instrumental-variable results are consistent with the benchmark regression results, but the causal interpretation should be treated with appropriate caution.

4.4. Heterogeneity Test

4.4.1. Firms' Technological Intensity

Firms' technological intensity may influence the effect of AI application on corporate ESG performance. Firms with lower technological intensity often face greater technological and resource constraints and may lack the innovation capabilities required to address ESG-related challenges effectively. These limitations may reduce their ability to identify and resolve environmental, social, and governance issues. However, AI technologies, including deep learning, big data analytics, and simulation, can provide such firms with new tools for technological upgrading and ESG management. By contrast, firms with higher technological intensity generally possess stronger knowledge bases and more advanced innovation capabilities. Because these firms already have relatively well-developed technological resources, the marginal contribution of AI application to ESG improvement may be less pronounced. Therefore, AI application is expected to generate a stronger ESG-enhancing effect among firms with lower technological intensity than among firms with higher technological intensity.

Accordingly, this study measures firms' technological intensity using the ratio of intangible assets to total assets. Based on the annual median of this indicator, the sample is divided into firms with higher and lower technological intensity to examine whether the effect of AI application on ESG performance differs across the two groups. As shown in columns (1) and (2) of Table 4, the coefficient of AI application is larger for firms with lower technological intensity than for those with higher technological intensity. This finding indicates that AI application generates a stronger improvement in ESG performance among firms with weaker technological foundations, consistent with the theoretical expectation.

Table 4. Heterogeneity test results.

	High Technol- ogy Intensity	Low Technol- ogy Intensity	Heavily Pol- luted Firms	Non-Heavily Polluted In- dustries	High Environ- mental Regulation	Low Environ- mental Regula- tion
	(1)	(2)	(3)	(4)	(5)	(6)
	ESG	ESG	ESG	ESG	ESG	ESG
AI	0.0027 *** (4.8996)	0.0038 *** (6.8038)	0.0019 *** (2.9262)	0.0034 *** (7.5077)	0.0033 *** (6.2642)	0.0027 *** (4.4199)
ROE	0.0024 (0.8522)	0.0024 * (1.8577)	0.0048 * (1.8893)	0.0026 (1.6340)	0.0027 * (1.8327)	0.0124 ** (2.1628)
Q	−0.0039 *** (−6.4441)	−0.0028 *** (−4.6393)	−0.0053 *** (−6.7662)	−0.0031 *** (−6.5521)	−0.0040 *** (−6.8481)	−0.0038 *** (−5.6938)
LEV	−0.0929 *** (−17.7128)	−0.0722 *** (−13.3083)	−0.0856 *** (−12.5467)	−0.0741 *** (−18.0823)	−0.0772 *** (−15.7164)	−0.0789 *** (−13.0096)
Boardsize	0.0003 (0.5965)	−0.0005 (−0.9677)	0.0008 (1.2204)	−0.0006 (−1.4955)	−0.0002 (−0.3041)	0.0002 (0.3183)
Institutional_share- holding	0.0002 *** (3.6584)	0.0003 *** (4.7976)	0.0002 *** (2.6494)	0.0002 *** (5.2204)	0.0002 *** (4.2684)	0.0002 *** (3.4975)
PGDP	0.0243 *** (4.3010)	0.0016 (0.2860)	0.0202 *** (3.0735)	0.0133 *** (2.9834)	0.0089 (1.5328)	0.0168 *** (2.8432)
Constant	4.0157 *** (62.7273)	4.2556 *** (66.2536)	4.0687 *** (54.7340)	4.1329 *** (81.0717)	4.1817 *** (63.4082)	4.1003 *** (60.9881)
Observations	21,936	22,115	11,873	32,992	25,410	18,393
R-squared	0.4180	0.4215	0.4130	0.4023	0.4237	0.4170
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

4.4.2. Degree of Industry Pollution

The effect of AI application on corporate ESG performance may vary according to the pollution intensity of the industry in which a firm operates. Heavily polluting industries are generally characterized by high energy consumption, substantial emissions, and greater exposure to environmental regulation. Firms in these industries often face stricter scrutiny from regulators and the public, creating strong pressure to improve energy efficiency and reduce pollutant emissions [45]. However, rigid production processes, legacy equipment, and the high cost of environmental transformation may constrain their ability to translate AI application into substantial ESG improvements. By contrast, firms in non-heavily polluting industries typically face lower environmental compliance costs and operate with more flexible production and management systems. Their ESG performance depends less on costly end-of-pipe pollution control and more on digital management, efficient resource allocation, information disclosure, supply-chain coordination, and governance optimization. AI can support these activities by improving operational efficiency, strengthening environmental monitoring, optimizing internal management, and enhancing ESG-related decision-making. Therefore, firms in non-heavily polluting industries may be better positioned to convert AI application into improved ESG performance, suggesting that the positive effect of AI is likely to be more pronounced in these industries.

Based on the Classification and Management List of Listed Companies in Environmental Verification Industries, this study divides the sample into firms operating in heavily polluting and non-heavily polluting industries to examine whether the effect of AI application on ESG performance varies with industry pollution intensity. As shown in columns (3) and (4) of Table 4, the coefficient of AI application is larger for firms in non-heavily polluting industries than for those in heavily polluting industries. This finding

indicates that AI application generates a stronger improvement in ESG performance among firms operating in industries with lower pollution intensity, consistent with the theoretical expectation.

4.4.3. Level of Regional Environmental Regulation

The effect of AI application on corporate ESG performance may vary with the strength of regional environmental regulation. Environmental regulation encompasses laws, regulatory requirements, policy incentives, subsidies, and other measures designed to limit corporate pollution, protect the environment, and encourage firms to assume greater social responsibility. In regions with stricter environmental regulation, firms face stronger compliance pressure and higher expectations regarding environmental and social responsibility [8]. Failure to meet these expectations may result in more frequent regulatory scrutiny, financial penalties, and reputational damage. To mitigate these risks, firms have stronger incentives to improve production processes, adopt intelligent manufacturing technologies, reduce pollutant emissions, and strengthen ESG management [10]. AI can support these efforts by improving environmental monitoring, compliance management, resource allocation, and production optimization. Therefore, the positive effect of AI application on corporate ESG performance is expected to be more pronounced in regions with stricter environmental regulation.

This study uses web-crawling techniques to identify and count keywords related to environmental regulation in the government work reports of Chinese prefecture-level cities. The resulting keyword frequency is used to measure the intensity of environmental regulation in each city. Based on the annual median of this measure, firms are classified into regions with higher and lower levels of environmental regulation, and separate regressions are conducted to examine whether the effect of AI application on ESG performance differs across the two groups. As shown in columns (5) and (6) of Table 4, the coefficient of AI application is larger for firms located in regions with stricter environmental regulation. This finding indicates that AI application has a stronger positive effect on corporate ESG performance in regions with higher environmental regulation, consistent with the theoretical expectation.

4.5. Mediation Effect Analysis

4.5.1. Testing the Mediation Effect of Human Capital Upgrading

Table 5 reports the regression results of the mediation test for human capital upgrading. Columns (1) and (3) examine the effect of AI application on the two measures of human capital upgrading, while columns (2) and (4) further include AI application and the corresponding human capital upgrading variable simultaneously in the ESG performance regression to test the mediation effect.

Specifically, column (1) of Table 5 shows that the coefficient of AI application on the number of highly educated employees is 0.2004 and is significant at the 1% level. This indicates that AI application significantly increases firms' demand for highly educated employees. Column (2) further examines the effect of AI application and the number of highly educated employees on ESG performance. The results show that the coefficient of the number of highly educated employees is 0.0209 and is significant at the 1% level, indicating that an increase in highly educated employees significantly improves firms' ESG performance. Meanwhile, the coefficient of AI application becomes statistically insignificant after the mediator is included, suggesting that the number of highly educated employees plays an important mediation role in the relationship between AI application and ESG performance.

Column (3) examines the effect of AI application on the percentage of highly educated employees. The coefficient of AI application is 0.0042 and is significant at the 1%

level, indicating that AI application also promotes the upgrading of firms' human capital structure by increasing the proportion of highly educated employees. Column (4) further includes both AI application and the percentage of highly educated employees in the ESG performance regression. The results show that the coefficient of the percentage of highly educated employees is 0.0159 and is significant at the 5% level, suggesting that the improvement in the proportion of highly educated employees contributes to better ESG performance. In addition, the coefficient of AI application remains significantly positive, indicating that the percentage of highly educated employees plays a partial mediation role.

Overall, the results support the mediation effect of human capital upgrading. AI application improves firms' ESG performance not only directly, but also indirectly by increasing both the number and the proportion of highly educated employees. This indicates that human capital upgrading serves as an important mediation path through which AI application enhances corporate ESG performance. Thus, H2 is supported.

Table 5. Mediation test results for the human capital upgrading channel.

	(1)	(2)	(3)	(4)
	Number of Highly Educated Employ- ees	ESG	Percentage of Highly Educated Employees	ESG
AI	0.2004 *** (32.2601)	0.0008 (1.2066)	0.0042 *** (4.1581)	0.0046 *** (7.7280)
Number of highly edu- cated employees	0.0209 *** (15.8196)			
Percentage of highly edu- cated employees			0.0159 ** (2.0320)	
ROE	0.0894 *** (2.6555)	0.0022 (0.6430)	0.0026 (0.5232)	0.0153 *** (2.7312)
Q	−0.0379 *** (−8.5278)	−0.0028 *** (−5.1220)	−0.0005 (−0.6415)	−0.0039 *** (−7.0205)
LEV	0.6259 *** (15.7876)	−0.0908 *** (−17.3446)	−0.0251 *** (−3.6227)	−0.0729 *** (−14.2320)
Boardsize	0.0385 *** (11.0887)	−0.0006 (−1.1104)	0.0025 *** (3.6141)	0.0001 (0.1254)
Institutional_sharehold- ing	0.0070 *** (16.2708)	0.0000 (0.5097)	0.0004 *** (5.4884)	0.0001 ** (2.5741)
PGDP	0.0713 * (1.7485)	0.0196 *** (3.4675)	0.0245 *** (3.6026)	0.0189 *** (3.3327)
Constant	1.0574 ** (2.2057)	3.9890 *** (61.5538)	−0.0829 (−1.0471)	4.0400 *** (62.4848)
Observations	26,693	25,060	26,665	25,032
R-squared	0.9309	0.4225	0.8848	0.4147
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

4.5.2. Testing the Mediation Effect of Green Technological Innovation

Table 6 reports the regression results of the mediation test for green technological innovation. Columns (1), (3), and (5) examine the effect of AI application on different types of green innovation, while columns (2), (4), and (6) further include AI application and the corresponding green innovation variable simultaneously in the ESG performance regression to test the mediation effect.

Specifically, column (1) of Table 6 shows that the coefficient of AI application on green innovation is 0.0045 and is significant at the 10% level. This indicates that AI application can promote firms' overall green innovation activities. Column (2) further examines the effect of AI application and green innovation on ESG performance. The results show that the coefficient of green innovation is 0.0041 and is significant at the 1% level, indicating that green innovation significantly improves firms' ESG performance. Meanwhile, the coefficient of AI application remains significantly positive, suggesting that green innovation plays a partial mediation role in the relationship between AI application and ESG performance.

To further examine the heterogeneous mediation effects of different types of green innovation, this study divides green innovation into inventive green innovation and utility green innovation. Column (3) shows that the coefficient of AI application on inventive green innovation is 0.0037 and is significant at the 10% level, indicating that AI application promotes firms' inventive green innovation. Column (4) further includes both AI application and inventive green innovation in the ESG performance regression. The coefficient of inventive green innovation is 0.0055 and is significant at the 1% level, suggesting that inventive green innovation significantly improves ESG performance. At the same time, the coefficient of AI application remains significantly positive, indicating that inventive green innovation also plays a partial mediation role.

Column (5) examines the effect of AI application on utility green innovation. The coefficient of AI application is 0.0319 and is significant at the 1% level, indicating that AI application significantly promotes utility green innovation. Column (6) further includes both AI application and utility green innovation in the ESG performance regression. The coefficient of utility green innovation is 0.0001 and is significant at the 10% level, suggesting that utility green innovation also contributes to the improvement of firms' ESG performance, although its effect is relatively weaker than that of inventive green innovation. The coefficient of AI application remains significantly positive, which indicates that utility green innovation also plays a partial mediation role.

Overall, the results support the mediation effect of green technological innovation. AI application improves firms' ESG performance not only directly, but also indirectly by promoting green innovation activities. Inventive green innovation and utility green innovation serve as partial mediation channels through which AI application enhances corporate ESG performance. Thus, H3 is verified.

Table 6. Mediation test results for the green technological innovation channel.

	(1)	(2)	(3)	(4)	(5)	(6)
	Green_Innovation	ESG	Inventive_Green_Innovation	ESG	Utility_Green_Innovation	ESG
AI	0.0045 *	0.0031 ***	0.0037 *	0.0031 ***	0.0319 ***	0.0031 ***
	(1.8903)	(8.4351)	(1.8426)	(8.4252)	(2.8220)	(8.4606)
Green_Innovation		0.0041 ***				
		(6.5517)				

Inventive_Green_ Innovation				0.0055 *** (7.4194)		
Utility_Green_ _Innovation					0.0001 * (1.8102)	
ROE	0.0089 * (1.9400)	0.0032 ** (2.0976)	0.0043 (1.4387)	0.0032 ** (2.1007)	0.0388 * (1.9084)	0.0032 ** (2.0968)
Q	0.0045 * (1.6760)	−0.0039 *** (−9.7590)	0.0029 (1.3036)	−0.0039 *** (−9.7558)	0.0513 *** (3.1102)	−0.0039 *** (−9.7202)
LEV	0.0173 (0.8465)	−0.0779 *** (−22.6851)	0.0194 (1.1499)	−0.0779 *** (−22.6983)	0.1428 (0.9305)	−0.0778 *** (−22.6455)
Boardsize	−0.0053 * (−1.8723)	−0.0000 (−0.0190)	−0.0060 ** (−2.3906)	0.0000 (0.0081)	0.0051 (0.2939)	−0.0000 (−0.0830)
Institutional_share- holding	0.0001 (0.3446)	0.0002 *** (6.4841)	0.0002 (1.0933)	0.0002 *** (6.4588)	−0.0004 (−0.2585)	0.0002 *** (6.4844)
PGDP	0.0098 (0.4273)	0.0143 *** (3.9805)	0.0316 * (1.6590)	0.0142 *** (3.9425)	−0.1217 (−1.0286)	0.0143 *** (3.9893)
Constant	0.1876 (0.7069)	4.1207 *** (100.3915)	−0.1452 (−0.6584)	4.1224 *** (100.4483)	1.3269 (0.9413)	4.1216 *** (100.333)
Observations	47,565	44,924	47,565	44,924	47,565	44,924
R-squared	0.6425	0.4006	0.6244	0.4008	0.4494	0.3999
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

5. Discussion

5.1. Research Conclusion

First, AI application has a positive impact on firm ESG performance. This conclusion still holds after replacing the explanatory variable, conducting the lag test, changing the sample period, excluding potential disturbing factors, and addressing the endogeneity problem. Therefore, AI application can help firms improve operational efficiency and ESG performance through deep learning, simulation, predictive analytics, and intelligent management. Although this study is based on Chinese A-share listed companies, the finding may also provide implications for countries that are simultaneously promoting digital transformation and sustainable development, such as India, Brazil, Indonesia, and Vietnam. In these economies, firms are also facing increasing pressure to improve environmental responsibility, social responsibility, and governance quality, while digital technologies are becoming important tools for corporate transformation. Therefore, AI may help firms in these countries improve ESG-related decision-making, resource allocation, operational monitoring, and information disclosure.

Second, AI shows a differentiated impact on firm ESG performance under different levels of firm technological intensities, industry pollution levels, and regional environmental regulation levels. Specifically, AI has a greater impact on the ESG performance of firms with lower technological intensity and a relatively smaller impact on firms with higher technological intensity. This indicates that AI may generate stronger marginal benefits for firms with weaker initial technological foundations. This finding may be particularly relevant to emerging economies and late-developing industrial economies, such as India, Vietnam, Indonesia, and South Africa, where firms' technological capabilities and digital infrastructure are still unevenly distributed. In such contexts, AI adoption may

help technologically weaker firms narrow capability gaps, improve management efficiency, and strengthen ESG-related practices.

In terms of industry pollution characteristics, AI shows a particularly significant ESG performance promotion effect on firms in non-heavily polluting industries, while its effect is relatively smaller among firms in heavily polluting industries. This suggests that the ESG-enhancing effect of AI is more easily realized in industries with relatively flexible production processes, lighter environmental compliance burdens, and stronger reliance on management optimization. This finding may be more relevant to economies with large service sectors, high-end manufacturing sectors, consumer industries, and light manufacturing industries, such as Singapore, South Korea, Japan, and Malaysia. For firms in these economies, AI may improve ESG performance mainly through governance optimization, supply-chain coordination, energy management, information disclosure, and stakeholder communication. By contrast, in countries with a relatively high share of resource-based or heavily polluting industries, such as South Africa, Indonesia, and Brazil, AI alone may not be sufficient to substantially improve ESG performance unless it is combined with cleaner production technologies, green investment, and stricter environmental regulation.

The empirical results also show that the enhancement effect of AI on firm ESG performance is more obvious in regions with higher environmental regulation. This finding may be particularly relevant to countries with relatively strict environmental regulation systems, stronger ESG disclosure requirements, and higher public pressure for corporate environmental responsibility, such as Germany, France, Japan, and South Korea. In these countries, external regulatory pressure can strengthen firms' incentives to use AI for environmental monitoring, pollution control, compliance management, and green innovation. However, in countries where environmental regulation is relatively weak or ESG disclosure enforcement is insufficient, the ESG-enhancing effect of AI may be less pronounced because firms may lack sufficient external motivation to apply AI technologies to sustainability-oriented activities.

Finally, the mediation effect analysis shows that AI affects firm ESG performance through two channels: promoting human capital upgrading and accelerating green innovation. On the one hand, AI significantly improves the firm labor force structure and increases the number of highly educated employees, which in turn accelerates the upgrading of the firm's human capital structure and ultimately improves firm ESG performance. On the other hand, AI promotes green technological innovation activities, which also improves firm ESG performance. This mediation effect may be especially relevant to countries that are trying to upgrade their labor force structure and strengthen green innovation capacity, such as India, Brazil, Vietnam, Malaysia, and South Africa. For these countries, the ESG value of AI depends not only on technology adoption itself, but also on whether firms and policymakers can strengthen digital skills training, attract high-quality human capital, support green R&D, and improve the institutional environment for sustainable innovation.

5.2. Theoretical Contributions

First, this study finds that AI application significantly improves corporate ESG performance. This result is consistent with previous studies showing that the digital economy and digital transformation can enhance ESG performance by improving operational efficiency, reducing information asymmetry, and strengthening stakeholder communication [9,10]. However, prior research generally treats digital technologies as a broad and relatively homogeneous category, leaving the specific sustainability implications of AI insufficiently examined. Unlike general digital technologies, AI can directly support prediction, pattern recognition, environmental monitoring, risk identification, resource allocation, and managerial decision-making [17,30]. By focusing on firm-level AI investment, this

study therefore extends the digital transformation literature by showing that ESG improvement arises not only from better information transmission, but also from the learning, prediction, and optimization capabilities embedded in AI. From a practical perspective, the finding implies that firms should integrate AI into environmental monitoring, risk management, information disclosure, and governance processes rather than treating it merely as a tool for cost reduction.

Second, this study identifies human capital upgrading and green technological innovation as two mediating paths through which AI improves ESG performance. Previous research on AI and employment has mainly examined whether AI substitutes for routine labor or increases the demand for highly skilled workers [27–29], whereas studies on AI and green innovation have focused primarily on whether AI promotes green technological development [24,25]. These two streams of research have rarely been connected to incorporate ESG outcomes within a unified framework. This study fills this gap by showing that changes in workforce structure and green innovation are not isolated consequences of AI adoption, but are important channels through which AI generates broader sustainability benefits. The findings also extend the automation–augmentation perspective [19] by indicating that AI creates greater ESG value when it complements highly educated employees. At the same time, the stronger contribution of inventive green innovation suggests that more substantive and knowledge-intensive innovation may generate greater ESG benefits than incremental technological improvements. These results imply that firms cannot rely on AI investment alone; they must also invest in employee skills, organizational learning, and green R&D capabilities.

Third, the heterogeneity results reveal important organizational and institutional boundary conditions. Existing research often assumes that firms with stronger technological capabilities are better able to absorb and benefit from new technologies [11]. However, this study finds that the ESG-enhancing effect of AI is stronger among firms with lower technological intensity. This suggests that AI may generate greater marginal benefits for technologically weaker firms by helping them overcome information-processing and managerial constraints. The stronger effect among non-heavily polluting firms also qualifies the expectation that AI should be most valuable in industries with the greatest environmental pressure. Although heavily polluting firms have stronger incentives to improve environmental performance, rigid production processes, legacy equipment, and high transformation costs may limit their ability to convert AI investment into ESG improvement [13,14,45]. In addition, the stronger effect in regions with stricter environmental regulation indicates that institutional pressure affects whether firms direct AI toward environmental monitoring, compliance management, and green innovation [8,10]. These findings extend prior studies that focus mainly on average technological effects by showing that the ESG value of AI depends on firms' technological foundations, industry characteristics, and regulatory environments. In practice, policy support should therefore be differentiated rather than uniform: technologically weaker firms may require capability-building assistance, while heavily polluting firms may need AI investment to be combined with cleaner equipment and process transformation.

Finally, this study contributes to the literature on responsible AI and corporate governance. Previous studies have emphasized that AI may generate risks related to energy consumption, labor displacement, algorithmic bias, privacy, transparency, and accountability [13,22,26]. These concerns provide an important alternative interpretation of the relationship between AI and ESG performance: AI may improve efficiency and reporting while simultaneously creating new environmental, social, and governance risks. The positive average effect identified in this study should therefore not be interpreted as evidence that all AI applications automatically enhance sustainability. Rather, the results suggest that AI generates ESG value when it is supported by complementary human capital, green

innovation, organizational governance, and environmental regulation. This shifts the theoretical question from whether AI is inherently beneficial or harmful to the conditions under which AI can produce substantive sustainability outcomes. For managers, this means that AI investment should be accompanied by data governance, ethical safeguards, human oversight, board-level supervision, algorithmic accountability, and environmental impact assessment. Otherwise, the potential ESG benefits of AI may be offset by new governance and ethical risks.

5.3. Policy Recommendations

First, governments can introduce targeted financial subsidies, tax incentives, and special funding programs to support the research, development, and application of AI within firms. Such policy support can reduce the initial costs and uncertainty associated with AI adoption and encourage firms to integrate AI into environmental monitoring, resource management, risk control, and ESG-related decision-making. Policy instruments should also be differentiated according to firms' technological capabilities and industry characteristics. In particular, firms with weaker technological foundations may require additional support for digital infrastructure, employee training, and organizational transformation, while firms in heavily polluting industries may need to combine AI investment with cleaner production equipment and process upgrading.

Second, government agencies, industry associations, and relevant experts should formulate standards and practical guidelines for the responsible application of AI in ESG-related activities. These guidelines should clarify requirements concerning data quality, privacy protection, algorithmic transparency, human oversight, accountability, and environmental impact assessment. A clearer governance framework can help firms understand the appropriate scope and potential value of AI while reducing ethical, operational, and compliance risks. In addition, regulators can encourage firms to disclose how AI is used in ESG management, thereby limiting the possibility that firms rely on AI only to improve ESG reporting without making corresponding improvements in their substantive practices.

Third, firms should integrate AI into their ESG management systems rather than treating it solely as a tool for automation or cost reduction. AI-enabled monitoring systems can be used to track energy consumption, pollutant emissions, workplace safety, supply-chain risks, and ESG-related information disclosure. These systems can help firms identify emerging risks, evaluate changes in ESG performance, and implement timely corrective measures. At the same time, firms should strengthen employee training, attract highly skilled personnel, and increase investment in green research and development so that AI can be effectively translated into human capital upgrading and green technological innovation. Through the joint development of technology, human resources, and governance capabilities, firms can more fully realize the potential of AI to improve ESG performance and support sustainable development.

5.4. Limitations and Future Research

This study has several limitations. First, the empirical analysis is based on Chinese A-share listed firms, and the findings may be influenced by China's specific institutional environment, ESG disclosure practices, regulatory framework, and digital infrastructure conditions. Therefore, caution is needed when generalizing the results to firms in other countries, unlisted firms, or small- and medium-sized enterprises. Second, corporate ESG performance is primarily measured using the Huazheng ESG rating database. Although this measure is appropriate for the Chinese market and the robustness test using Bloomberg ESG scores yields consistent results, ESG ratings may vary across providers because of differences in methodologies and indicator weights.

In addition, although this study uses lagged regressions, PSM-DID analysis, and an instrumental-variable approach to mitigate endogeneity concerns, full causal identification remains difficult in an observational panel data setting. In particular, the Kleibergen–Paap rk Wald F statistic is below the conventional threshold of 10, indicating a potential weak-instrument concern; therefore, the IV results should be interpreted with caution despite the supportive weak-instrument-robust tests. Future research could use cross-country samples, multiple ESG data sources, more detailed measures of AI application, and quasi-natural experiments or policy shocks to provide stronger evidence on the causal effects and boundary conditions of AI application on corporate ESG performance.

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