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AI-Driven Corporate Sustainability: Exploring the Moderating Role of External Regulation

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Abstract

This paper investigates Artificial Intelligence's (AI) systemic impact on corporate Environmental, Social, and Governance (ESG) performance. Analyzing Chinese-listed companies from 2013 to 2022, we find that AI adoption significantly promotes ESG outcomes. Both 'soft' regulation (investor attention) and 'hard' regulation (environmental regulation) significantly strengthen this contribution. Notably, investor attention exhibits a complex threshold effect: at lower levels of attention, AI adoption negatively impacts ESG performance, suggesting that firms may prioritize efficiency over sustainability in the absence of public scrutiny. The facilitative effect only emerges once investor attention surpasses a critical threshold, highlighting AI's 'double-edged sword' nature. For 'hard' regulation, environmental regulation positively moderates AI's impact on environmental and governance performance but lacks a similar effect on social performance. Furthermore, AI primarily drives social and governance goals in non-state-owned enterprises (non-SOEs), while its impact in state-owned enterprises (SOEs) is concentrated in the environmental dimension. These results underscore that AI's transformative potential is contingent upon regulatory frameworks and ownership-specific institutional logics.

Keywords: artificial intelligence, ESG, investor attention, environmental regulation, moderating effects, SOEs

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Introduction

Balancing social development with environmental sustainability has become a critical challenge in the face of a growing global population. Human activities have led to environmental pollution, global warming, resource depletion, and biodiversity loss, which now hinder societal progress and create substantial barriers to sustainable development. In this context, ESG practices have become essential mechanisms for tackling global climate challenges and achieving carbon neutrality, forming the cornerstone of sustainable development strategies worldwide. For corporations, which are an important component of national economic development, ESG transformation is not only a matter of corporate value [1] and sustainability [2], but also an integral part of national economic progress and international reputation. Thus, corporations are now expected to balance financial performance with sustainable development goals.

As of June 10, 2024, 2,090 publicly listed companies in China's A-share market had issued ESG reports, representing 38.9% of all A-share companies. Despite this progress, as the largest emerging market globally, China remains in the early stages of ESG development. Encouraging broader participation in ESG practices has become a key challenge in achieving the nation's sustainability goals. With the increasing global emphasis on ESG, several studies have explored the factors influencing ESG performance. Internal factors like firm size [3], financial performance [4], governance structure [5; 6], and ownership structure [7] have been shown to impact ESG outcomes. External influences, including market competition [8], fintech adoption, government policies [9; 10], regulatory enforcement, media coverage [11], and investor attention [12], have also been extensively examined.

In addition to these factors, digital transformation has garnered significant attention for its positive impact on ESG performance [13–16]. However, the impact of AI, a more advanced subset of digital technology, remains in an exploratory phase in terms of its application at the corporate level. AI integrates theories, technologies, and practical applications designed to mimic, enhance, and expand human intelligence [17], thereby enabling deeper data collection and interaction [18]. As a key driver of productivity across industries [19], AI is reshaping business operations and models [20]. Although studies have shown that AI significantly enhances processes, increases efficiency, reduces costs, and improves competitiveness [21; 22], research on AI's impact on corporate ESG remains limited.

The European Union's 'Expert Group's Policy and Investment Recommendations for Trustworthy AI' (the Guidelines) underscore the necessity of acknowledging a diverse array of stakeholders – including society at large, living organisms, and the natural environment – across the entire lifecycle of an AI system. These Guidelines advocate for the integration of sustainability and ecological considerations in AI applications [23]. To date, much of the research on AI's influence on sustainability has focused on specific macro-level domains [24] like the labor market [25], carbon emissions [16; 26; 27], pollution control [28], and pollution forecasting [29]. In contrast, data at the corporate level remains relatively scarce [30], with studies being more fragmented and not drawing consistent conclusions. Another major limitation of the existing literature is its tendency to view AI as a collection of isolated task-automation tools, rather than a General-Purpose Technology (GPT) that permeates systemic organizational routines.

Several studies have concluded that AI holds significant potential in promoting corporate environmental sustainability [31; 32], optimizing employee work environments and fairness [33; 34], enhancing customer satisfaction [35], and strengthening internal governance efficiency [36]. However, it has also been shown to present significant challenges related to ESG factors, encompassing issues such as corporate governance, human rights, labor practices, environmental ramifications, equitable business operations, and consumer rights [37]. These challenges underscore a potential "digitalization paradox" where firms, driven by managerial myopia, may prioritize technological efficiency over sustainable development [38; 39]. Consequently, the net impact of AI on corporate ESG is not inherently positive but is contingent upon the firm's external institutional environment and internal governance logic. The balance between AI's potential contributions and the ESG risks it introduces remains the subject of a critical inquiry.

Given the inherent trade-offs between technological efficiency and social externalities, corporate sustainability cannot be achieved in an institutional vacuum [40]. In emerging markets like China, characterized by voluntary ESG disclosure and high information asymmetry, the governance of advanced technologies requires a synergistic blend of formal and informal oversight. Specifically, governmental environmental regulation (hard regulation) provides a mandatory compliance floor, while investor attention (soft regulation) serves as a potent informal monitoring mechanism that disciplines managerial short-termism and opportunistic behavior [41]. We contend that these regulatory forces function as essential institutional anchors that determine the 'strategic direction' of AI adoption. In an environment with robust oversight, the reputational and political costs of non-compliance are significantly heightened, compelling firms to channel AI's analytical power toward substantive sustainability improvements rather than narrow profit maximization. Despite the critical importance of these regulatory moderators, empirical evidence on how they interact with the technological dividends of AI to shape multi-dimensional ESG outcomes remains absent from the current literature.

This paper makes several contributions:

First, it provides a novel and comprehensive analysis of AI's role in improving ESG performance, exploring both its potential and challenges and addressing the fragmented insights in existing research. While most prior studies have focused on AI's impact on economic or environmental outcomes, this research uniquely explores AI's effects across all three ESG dimensions at the corporate level. Second, this paper examines the moderating effects of external regulation – both hard (governmental environmental regulation) and soft (investor attention) – on the link between AI implementation and ESG. This exploration sheds light on how external governance mechanisms influence the effectiveness of AI in driving sustainable development, providing a nuanced perspective on the interaction between technological innovation and regulatory environments. This theoretical advancement emphasizes the critical role of external regulation in shaping AI's contributions to sustainable development. Thirdly, this study provides a deeper heterogeneity analysis by exploring how divergent institutional logics (SOEs vs. non-SOEs) shape the strategic implementation of AI. The study uncovers significant differences in AI's impact on ESG performance across firms with varying ownership structures due to different regulatory and competitive pressures. This result provides practical guidance for tailoring AI-driven strategies across different firm types.

Literature review and research hypotheses

The impact of artificial intelligence on ESG

This study conceptualizes Artificial Intelligence (AI) not merely as a collection of isolated software applications, but as a General-Purpose Technology (GPT) that functions as a systemic catalyst for corporate ESG transformation. Unlike traditional Information Technologies (IT) that focus on specific task automation, AI is characterized by its pervasiveness, capacity for continuous improvement, and ability to generate innovative complementarities across diverse business functions [42; 43].

At the theoretical level, we define a firm's AI adoption as a systemic strategic orientation. According to the Attention-Based View (ABV) of the firm, the issues that command the strategic attention of top decision-makers determine the direction of organizational resource allocation and subsequent corporate behavior [44]. Therefore, the intensity of a firm's commitment to AI represents a high-order organizational capability – aggregate digital intelligence intensity – which permeates the firm's strategic infrastructure and organizational routines. Drawing on the Resource-Based View (RBV), we argue that this capability enables firms to transcend the traditional trade-offs between economic efficiency and sustainability goals [45; 46]. AI-driven ESG transformation operates through three core theoretical mechanisms:

First, the enhancement of information processing capabilities. According to Information Processing Theory, the complexity of ESG management stems from the vast, unstructured, and multi-dimensional nature of sustainability data [47]. AI provides the computational power necessary to internalize these social externalities by converting massive datasets into actionable strategic insights. By reducing information asymmetry between internal management and external stakeholders, a robust AI orientation enables firms to identify latent environmental risks and social needs more precisely, thereby improving the quality and transparency of ESG disclosures.

Second, the optimization of resource allocation and the "Green Digital Twin" effect. AI shifts the firm's production possibility frontier by enabling hyper-efficiency. Through predictive analytics and intelligent coordination, AI allows for a "digital-sustainability twin transition", where technological optimization directly translates into resource conservation and emission reduction [48]. This systemic optimization extends from shop-floor energy management to complex global supply chain auditing, fostering a holistic approach to value creation that satisfies both shareholders and broader stakeholders.

Third, the mitigation of agency costs and decision-making biases. Corporate governance often suffers from the bounded rationality of human managers and the agency problems inherent in the separation of ownership and control. AI functions as an "augmented intelligence layer" for the board and management, providing an objective, data-driven perspective that curbs managerial short-termism and cognitive biases [36; 49]. By automating compliance and monitoring executive behavior, AI enhances organizational integrity, which is a cornerstone of robust ESG performance.

However, the theoretical relationship between AI and ESG is not purely linear. As a double-edged sword, the deployment of AI involves significant institutional and environmental costs, such as a massive energy footprint and the potential for algorithmic opacity [50; 51]. We contend that the net effect of AI on ESG is a dynamic balance between these technological dividends and systemic costs. In an ideal institutional environment, as suggested by the Innovation Compensation Effect [52], the long-term gains from AI-driven green innovation are expected to outweigh the inherent costs of implementation. Therefore, we propose:

Hypothesis 1: *Artificial intelligence improves corporate overall ESG performance.*

The role of AI in shaping environmental performance

Artificial Intelligence (AI) presents a dual environmental impact: while it provides innovative solutions to reduce emissions and increase the efficiency of pollution and waste management, its deployment also generates significant energy consumption and emissions [53], creating a disruptive effect on the environment.

At the operational core, AI serves as a critical tool for advancing energy efficiency and cleaner production. By deploying machine learning algorithms for real-time monitoring of energy consumption patterns, firms can significantly reduce resource intensity and carbon emissions [31; 32; 54]. AI technologies enable precise forecasting of energy demand and optimize the scheduling of clean energy systems, thereby reducing the carbon footprint of internal manufacturing processes [26; 55]. Furthermore, AI-driven waste management systems allow for the precise tracking of pollutants and packaging materials, minimizing toxic emissions at the source [56]. However, AI's environmental contributions come at a cost. According to the rebound effect theory, AI's application improves energy efficiency and reduces costs, which leads to an expansion of overall energy demand, ultimately exacerbating pollution. Furthermore, the infrastructure required for AI demands substantial energy and leads to the increase of electronic waste, thus creating a large carbon footprint [50] as well as hazardous materials like lead, arsenic, mercury, and cadmium [37; 57], posing considerable environmental risks.

Beyond internal boundaries, AI reshapes environmental performance through enhanced supply chain transparency and coordination. By improving demand forecasting and logistics routing, AI minimizes inventory waste and logistics-related carbon emissions [56; 58; 59]. More importantly, AI-enabled monitoring allows firms to evaluate the environmental credentials of upstream suppliers more accurately, reducing the ecological footprint of the entire value chain. This collaborative green synergy ensures that environmental gains are not localized but are distributed across the supply network, fostering a holistic approach to waste reduction and carbon management [60].

On a broader level, the integration of AI facilitates sustainable practices throughout the product lifecycle, from smart location planning to post-market recycling systems [56]. These technologies support firms in aligning their environmental output with regional and national sustainability goals, such as China's carbon peaking and carbon neutrality objectives [55; 61]. By providing data-driven insights into product lifecycle impacts, AI enables companies to transition from reactive pollution control to proactive environmental stewardship.

In summary, although the pathways through which AI affects the environment are multi-dimensional, encompassing internal efficiency, supply chain transparency, and societal alignment, these mechanisms are fundamentally driven by the firm's overall digital intelligence capacity. We contend that the frequency of AI-related keywords in annual reports reflects the depth of a firm's strategic commitment to embedding these technologies into its sustainability framework.

However, it is crucial to recognize that the net environmental contribution of AI is not an automatic outcome; it represents a dynamic balance between technological dividends and inherent energy costs. The realization of AI's green potential is contingent upon whether the efficiency gains can effectively offset the rebound effect and the heavy energy footprint of digital infrastructure. This balance is often dictated by the external institutional environment and monitoring intensity, which determine whether AI is deployed for narrow production expansion or meaningful green transformation. In the absence of sufficient oversight, firms may prioritize short-term efficiency over long-term ecological integrity. Nevertheless, assuming a baseline level of corporate responsibility and the overarching trend of green digitalization, we argue that higher AI integration provides the necessary systemic advantage to optimize environmental management. Therefore, we propose:

Hypothesis 2: *Artificial intelligence improves corporate environmental performance.*

The role of AI in shaping social performance

Within the organization, AI functions as a critical asset for fulfilling internal social responsibilities. By substituting human labor in hazardous, toxic, or high-risk environments, AI fundamentally enhances workplace safety and reduces occupational hazards [33; 62]. Moreover, the automation of repetitive and high-intensity tasks through AI-driven systems reduces the physical and mental workload of employees, thereby contributing to enhanced job satisfaction and overall well-being [34; 49; 62]. Beyond efficiency, AI-enabled text mining and emotional analysis allow for a more dynamic understanding of employee morale, facilitating proactive management of the work environment [63]. While concerns regarding algorithmic bias in recruitment and potential privacy infringements through surveillance persist [64–66], the strategic integration of AI typically signifies a move toward more data-driven and safety-oriented human resource management.

At the supply chain level, AI acts as a mechanism for ethical oversight and transparency. Real-time monitoring capabilities enable firms to trace the sourcing of raw materials with unprecedented precision, ensuring that upstream partners adhere to ethical labor standards and human rights policies. This systemic traceability mitigates risks associated with labor exploitation and strengthens the integrity of the entire supply chain. Furthermore, AI enhances a firm's responsiveness to consumer needs by capturing real-time feedback through sentiment analysis. This customer-centric orientation allows firms to align their operational strategies with the evolving social expectations of their stakeholders, thereby improving post-sales support and the overall customer experience [67].

On a broader societal level, the impact of AI is characterized by the tension between productivity enhancement and labor disruption. Existing theories suggest that AI can catalyze societal well-being by improving service quality and fostering economic growth. Although the current trajectory of AI development often prioritizes automation, potentially reducing opportunities for low-skilled workers and exacerbating income inequality [68], it also creates a productivity effect that can stimulate labor demand in new, high-value-added sectors [69, 70]. The net social impact of AI at the societal level thus depends on a firm's capacity to balance technological efficiency with its broader commitment to community welfare and human rights [71–73].

In conclusion, while the social implications of AI are multi-faceted and involve significant ethical trade-offs, they are fundamentally driven by the firm's aggregate digital intelligence capability. A higher intensity of AI adoption indicates a more robust infrastructure for monitoring safety, ensuring supply chain ethics, and responding to stakeholder feedback. Despite the risks of algorithmic bias or privacy concerns, we argue that AI's potential for systematic social coordination provides a net positive contribution to corporate social performance. Therefore, we propose the following hypothesis:

Hypothesis 3: *Artificial intelligence improves corporate social performance.*

The role of AI in shaping governance performance

The influence of AI on corporate governance represents a systemic shift from traditional human-centric oversight to a data-driven governance paradigm. Within the framework of corporate sustainability, AI transcends its role as a functional tool to become a strategic asset that optimizes internal power structures and decision-making efficiency [74]. This study contends that a firm's aggregate AI strategic orientation, captured by its AI keyword intensity, serves as a robust proxy for the modernization and transparency of its governance infrastructure.

At the core of modern governance is the challenge of making sound business judgments amidst high complexity. AI facilitates this by harnessing powerful data analytics and forecasting capabilities, allowing boards to capture critical insights that remain obscured in traditional reporting [49]. By automating the processing of extensive corporate data, AI helps to flatten organizational management, reduce internal information asymmetry, and improve the overall accuracy of strategic decisions [75; 76]. Furthermore, AI provides corporate managers with an external perspective, reducing cognitive biases and subjectivity in major governance choices [77]. As suggested by Hilb [36], AI-driven decision-making supports the evolution of governance processes by providing a more scientifically grounded basis for long-term development.

However, the integration of AI into governance also introduces specific technological risks. The black-box nature of complex algorithms can create opacity, potentially leading to accountability issues and reducing stakeholder trust in AI-driven outcomes. Moreover, there is a risk of managerial manipulation, where management might selectively control AI inputs or data sources to align with self-serving interests, potentially compromising the integrity of internal controls [78].

Despite these risks, we argue that a higher intensity of AI adoption indicates that a firm has invested in the necessary digital infrastructure to automate compliance and optimize board oversight. These systemic improvements in information transparency are expected to outweigh the risks of algorithmic opacity, leading to higher overall governance scores. Thus, we propose:

Hypothesis 4: *Artificial intelligence improves corporate governance performance.*

The moderating effect of investor attention

ESG inherently carries significant positive externalities, reflecting a firm's contributions to long-term sustainability and broader social and environmental goals. However, these positive externalities are often accompanied by increased short-term costs, which may deter companies from voluntarily undertaking these initiatives in the absence of external incentives or regulations. Furthermore, the inherent tension between a company's short-term profit objectives and ESG's long-term sustainability goals often leads firms to prioritize using AI technologies to optimize operating efficiencies and profitability while underinvesting in ESG-related applications. However, investor attention serves as an informal supervisory mechanism [79] that can exert compliance pressure on publicly listed companies [12], safeguard the rights of stakeholders, and compel firms to assume greater responsibility for their ESG performance [80].

The extensive adoption of the Internet and social media has played a key role in increasing institutional pressure on firms to fulfill their corporate social responsibility [81; 82]. The significant public pressure generated by increased attention acts as a form of external soft supervision. This external supervision reduces information asymmetry, decreases the likelihood of corporate misconduct [83; 84], and curbs opportunistic behavior by management [85], compelling firms to realign their behavior to align with social ethics, thereby enhancing their environmental and social responsibility [12; 84; 86; 87], encouraging firms to leverage AI technology to enhance ESG performance and expedite long-term sustainable development goals.

Moreover, increased investor attention enhances transparency and accountability, thus mitigating information asymmetry and building investor confidence, which can positively influence a company's access to financial resources [88]. These additional resources can be strategically directed toward the adoption and implementation of AI technologies that enhance ESG efforts, such as real-time monitoring of environmental impacts or optimizing governance frameworks. By leveraging both financial and technological resources, firms can better integrate ESG principles into their operations and achieve more sustainable long-term development [82].

Based on this rationale, this study proposes the following hypothesis:

Hypothesis 5: *Investor attention positively moderates the relationship between AI and corporate ESG performance.*

Hypothesis 6: *Investor attention positively moderates the relationship between AI and corporate environmental performance.*

Hypothesis 7: *Investor attention positively moderates the relationship between AI and corporate social performance.*

Hypothesis 8: *Investor attention positively moderates the relationship between AI and corporate governance performance.*

The moderating role of environmental regulation

Environmental resources possess the characteristics of public goods and externalities, so when penalties for non-compliance are minimal, companies are rationally inclined to adopt a "pollute first, mitigate later" strategy [89]. Ample evidence suggests that in the early 21st century, Chinese companies preferred paying fines for breaching national standards instead of investing in wastewater treatment facilities to manage and reduce pollution [90]. However, as local governmental pressure for environmental regulation intensified, companies became more likely to implement proactive pollution prevention measures instead of solely relying on end-of-pipe solutions [91]. Consequently, without strict legal environmental regulations, the efficacy of AI in enhancing ESG performance may be constrained.

Complying with environmental policies is not only a legal obligation but also a strategic move for businesses [92]. Motivated by compliance, companies are more likely to apply AI technologies in environmental management, leveraging AI to drive green innovation, enhance smart pollution control, and improve resource and energy efficiency to avoid non-compliance risks. However, some studies suggest that while environmental regulation can improve environmental performance, it also raises the cost of environmental management for firms [93], leading to substantial compliance costs that may crowd out productive expenditures [93; 94], which, in turn, could reduce firms' investment in social responsibility and compliance governance [93]. Conversely, other research indicates that environmental regulation can improve the overall performance of ESG [95].

Despite these differing views, we hypothesize that environmental regulation positively moderates the relationship between AI adoption and ESG performance. This hypothesis is grounded in the notion that environmental regulation acts as a critical signal, reflecting the government's prioritization of sustainability and long-term economic strategy. By capturing this signal, firms are incentivized to not only comply with environmental policies but also recognize the broader value of social responsibility and governance reforms. Regulatory pressure encourages firms to deploy AI technologies more holistically across ESG dimensions to ensure rapid response to government strategies and alignment with policy objectives and to avoid compliance risks.

Based on these considerations, the following hypotheses are proposed.

Hypothesis 9: *Environmental regulation positively moderates the relationship between AI and corporate ESG performance.*

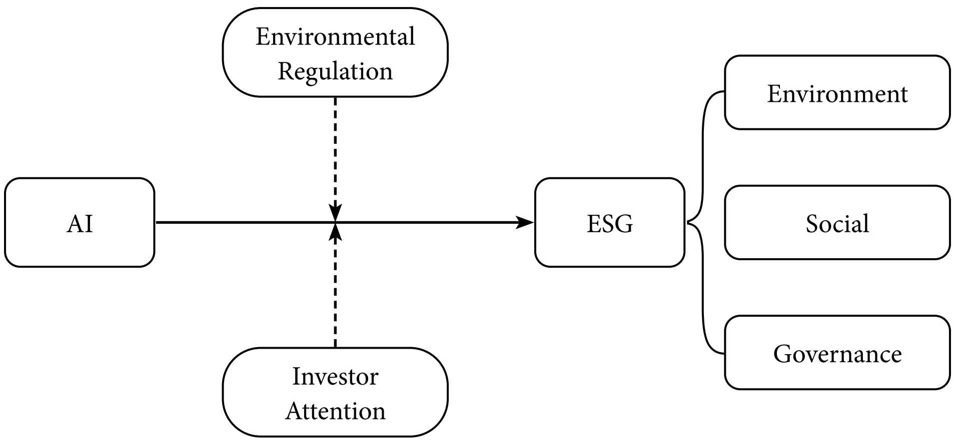
Hypothesis 10: *Environmental regulation positively moderates the relationship between AI and corporate environmental performance.*

Hypothesis 11: *Environmental regulation positively moderates the relationship between AI and corporate social performance.*

Hypothesis 12: *Environmental regulation positively moderates the relationship between AI and corporate governance performance.*

Based on the above hypotheses, the research model is depicted in Figure 1.

Figure 1. Research model



Research design

Data sources

This study focuses on A-share listed companies from 2013 to 2022 to investigate the influence of AI on ESG performance. The year 2013 was chosen as the starting year because it represents a critical moment in the evolution of deep learning technology, which has become foundational to modern AI advancements. Additionally, 2013 marks the beginning of China's 4G network construction, which, alongside the rapid development of mobile internet technology, provided crucial infrastructure and data support for AI applications [96]. AI data were manually collected by the research team, while other related data came from the Wind financial terminal and CSMAR databases. The sample selection follows these criteria: 1) excluding samples with insufficient data; 2) excluding financial and insurance companies due to their particular characteristics [97–99]; 3) excluding ST, PT, and *ST companies [100; 101]; 4) to reduce the impact of outliers, all continuous variables were adjusted using winsorization at the 1 and 99% [102; 103]. Since Bloomberg only provides ESG ratings for a subset of Chinese listed companies, the final sample size is relatively small. The final dataset includes 1148 companies with a total of 8906 observations. All empirical analyses were conducted using Stata 17.0 software.

Description of variables

Dependent variable: This study utilizes Bloomberg's ESG database as the primary data source of ESG variables. First, Bloomberg's ESG database adopts one of the most comprehensive approaches for evaluating companies' ESG activities and outcomes, offering a rigorous and systematic evaluation framework [104]. Second, Bloomberg has been conducting ESG ratings since 2008, providing a long time span that ensures consistent and reliable data for the study [105]. The database encompasses over 2,000 data points in areas ranging from air quality and climate change to water and energy management, employee health and safety, and board structure, among others. These rich and diverse data points enable a comprehensive analysis of firms' performance across the different dimensions of ESG.

To ensure the robustness of our findings, we use Huazheng ESG ratings instead of Bloomberg ESG ratings for robustness checks. Huazheng ESG rating is one of the most advanced ESG indices in China and has been widely used in multiple studies to assess firms' ESG performance [106–108]. This rating system ranks companies from AAA to C across nine levels, with assessments conducted quarterly, thus providing more timely data. For this study, we assigned values from 1 to 9 according to these ratings, using the annual average score as the firm's ESG performance for each year.

Explanatory variable: Artificial Intelligence (AI). The growing use of text analytics and machine learning in economics has made it possible to utilize big data text mining to assess AI adoption in publicly listed companies through their annual reports. Referring to existing literature [109–111], this study constructs a firm-level AI index using machine learning and text analysis techniques. The words used in a company's annual report can reflect its business philosophy and developmental trajectory [38]. This approach allows for an accurate capture of a firm's actual investment in and application of AI technologies, offering a precise representation of the depth and breadth of AI utilization within the company. Based on Yao et al.'s [112] study that identified 73 AI-related keywords (see Table 1), we applied the open-source Python "jieba" Chinese word segmentation tool to analyze annual reports from 2013 to 2022. To avoid ambiguity caused by the broad meanings of some commonly used words, this study manually filtered out words that were less relevant to AI applications. For example, the term "artificial intelligence" was matched with the phrase "Artificial Intelligence Co., Ltd.", and its frequency was calculated. Then, such expressions were excluded from the overall frequency of the "artificial intelligence" keyword. This process was repeated to obtain the final adjusted frequency for each term. Then we calculated the frequency of AI-related terms (including their abbreviations) within the reports and determined the total number of words in the report. The ratio of AI-related terms to the total word count was then logarithmically transformed, providing a proxy for the level of AI application. That is:

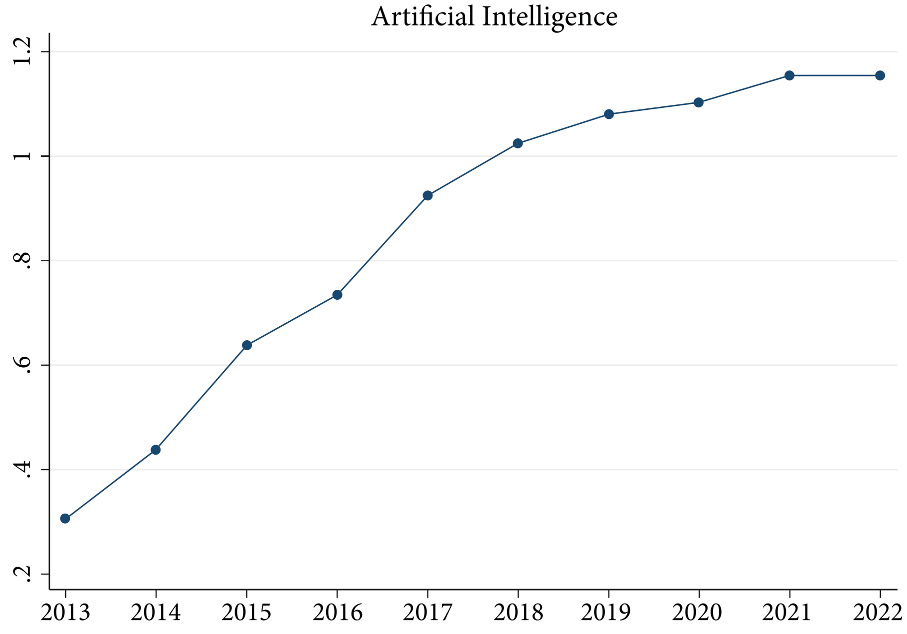
$$AI = \ln\left[\frac{\left(\sum_{n}^{73} Keyword\ frequency\right)}{total\ words} + 1\right]. \quad (1)$$

Table 1. Keywords for Artificial Intelligence

Keyword thesaurus				
Artificial Intelligence (AI)	Computer Vision	Image Recognition	Knowledge Graph	Intelligent Education
Augmented Reality (AR)	Intelligent Government	Feature Extraction	Business Intelligence	Smart Elderly Care
Support Vector Machine (SVM)	Knowledge Representation	Pattern Recognition	Internet of Things (IoT)	Human-Computer Dialogue
AI Products	Human-Computer Interaction	Data Mining	Smart Banking	Intelligent Customer Service
Virtual Reality (VR)	Autonomous Driving	Driverless Driving	Smart Finance	Big Data Marketing
Long Short-Term Memory (LSTM)	Smart Chips	Edge Computing	Cloud Computing	Deep Neural Networks (DNN)
AI Chips	Deep Learning	Feature Recognition	Smart Insurance	Intelligent Retail

Keyword thesaurus				
Intelligent Healthcare	Smart Transportation	Smart Home	Recurrent Neural Networks (RNN)	Big Data Risk Control
Robotic Process Automation (RPA)	Wearable Products	Big Data Platform	Augmented Intelligence	Big Data Operations
Machine Translation	Neural Networks	Speech Synthesis	Human-Machine Collaboration	Smart Agriculture
Natural Language Processing (NLP)	Convolutional Neural Networks (CNN)	Question Answering System	Reinforcement Learning	Big Data Analysis
Smart Speaker	Big Data Management	Intelligent Computing	Voice Interaction	Machine Learning
Biometric Recognition	Smart Environmental Protection	Intelligent Regulation	Intelligent Investment Advisor	Speech Recognition
Voiceprint Recognition	Facial Recognition	Intelligent Agent	Big Data Processing	Distributed Computing
Intelligent Sensors	Intelligent Search	Smart Voice		

Figure 2. Average AI adoption trend at listed companies in China, 2013–2022



The trend in average AI adoption levels of companies from 2013–2022 is shown in Figure 2, with the vertical axis showing the AI keyword frequency ratio. In 2013, the sample average was 0.307, while in 2022, it was 1.154.

Moderator variable: Investor Attention (Inv_Att). Web search volume reflects the search behavior of Chinese netizens and serves as a direct and effective measure of public attention [113; 114]. By March 2024, China had

1.232 billion active mobile internet users, making search volume a widely accepted indicator of investor attention. Retail investors, who dominate China's capital market, often face information asymmetries and primarily use web searches to gather company-related information for investment decisions. Based on previous research [115-117], we manually collected data from the "Baidu Index" (https://index.baidu.com) for this variable. Specifically, we entered stock codes, company abbreviations, and full company names into the Baidu Index platform to retrieve the number of searches during a specified period and summed the search values for these keywords, applying a natural logarithm transformation. This approach is adapted from Da's [118] study on manually collecting Google search volume. Higher web search volume indicates that the company has likely attracted greater investor attention [113; 119].

Environmental Regulation (ER). Consistent with Liu et al. [99], we measure the intensity of ER using the ratio of investment in wastewater and air pollution control to industrial output in the provinces where listed firms are located. This ratio reflects the local government's efforts and enforcement strength in environmental management. A higher ratio indicates stronger environmental regulation in that area. Relevant data are from the China Provincial Database.

Control variables: Based on existing studies [97; 100], we incorporate the following control variables: to capture profitability, we use return on assets (ROA) and revenue growth rate (Growth). Future growth opportunities are measured by Tobin's Q (TobinQ). We also incorporate firm-level characteristics such as firm size (Size), firm age (Age), and leverage ratio (Lev) to control for the impact of financial indicator changes on ESG. We also introduce governance variables, including board of directors (Boa_Dir), board of directors' independence (Ind), shareholding concentration (Top 1), and CEO duality (CEO_duality). These variables collectively provide a comprehensive framework for analyzing the factors affecting ESG metrics. The definitions and quantification of all variables are presented in Table 2.

Table 2. Variable definitions

Variable Type	Variable Name	Variable Symbol	Variable Description
Dependent variables	Bloomberg ESG performance	ESG	Bloomberg ESG combined score
	Environmental performance	Environment	Bloomberg ESG environment score
	Social performance	Social	Bloomberg ESG social score
	Governance performance	Governance	Bloomberg ESG governance score
	Huazheng ESG	ESG_hz	Huazheng ESG combined score
Explanatory variable	Artificial Intelligence	AI	The ratio of the word frequency of AI-related keywords to the total word frequency of the annual report is log-transformed.
Moderator variables	Investor Attention	Inv_Att	The logarithmic transformation of web search volumes for company-related keywords
	Environmental regulation	ER	Proportion of the amount invested in wastewater and exhaust gas pollution control in the provinces where listed firms are located to the industrial output value in the current year, and taking natural logarithms.

Control variables	Enterprise size	Size	ln (Total assets)
	Enterprise age	Age	Years of observation minus the year of listing and taking natural logarithms
	Gearing	Lev	Total liabilities divided by total assets
	Return on total assets	ROA	Net profit divided by total assets
	Growth rate of revenue	Growth	(Current operating income minus previous operating income) divided by previous operating income
	Future growth opportunities	TobinQ	Market value of assets divided by replacement cost of assets
	Board of directors	Boa_Dir	Number of Board of Directors
	Board independence	Ind	Number of independent directors divided by number of directors
	Shareholding concentration	Top1	Proportion of shares held by the largest shareholder of the enterprise
	CEO duality	CEO_duality	When the CEO of a company simultaneously holds the position of chairman of the board of directors, it is referred to as CEO duality, which takes the value "1", otherwise, it takes the value "0".

Note: The table comprehensively explains and quantifies all the variables used in the empirical analysis.

Table 3. Descriptive statistics of the variables

Variables	Obs	Mean	Std. Dev	Min	Max
ESG	8.906	30.37	10.35	0	73.38
Environment	8.906	13.35	15.63	0	76.71
Social	8.906	14.67	8.217	0	63.09
Governance	8.906	67.09	15.46	0	96.12
AI	8.906	0.464	0.543	0	1.914
ESG_hz	8.906	4.398	1.021	1	8
Inv_Att	8.906	3.356	4.008	0	17.02
ER	8.906	9.054	3.220	0	12.07
Size	8.906	23.32	1.410	20.55	28.15
Age	8.906	1.740	0.511	0.693	2.398
Lev	8.906	0.478	0.205	0.0750	0.929
ROA	8.906	5.572	5.273	-5.167	25.04
Growth	8.906	0.346	0.866	-0.630	5.832
Tobin Q	8.906	1.995	1.459	0	8.909
Boa_Dir	8.906	8.975	1.913	3	19
Ind	8.906	0.376	0.056	0.167	0.8
Top 1	8.906	0.358	0.159	0.034	0.90
CEO_duality	8.906	0.269	0.443	0	1

Descriptive statistics of the variables

Table 3 presents descriptive statistics for the dataset's 8,906 observations. The average ESG score is 30.37, with a standard deviation of 10.35, indicating substantial variation in ESG performance in the sample. The average for AI is 0.464, signifying that the average frequency share of AI-related keywords is 0.87%, with a range from 0 to 5.78%. The average scores for environmental performance and social performance are 13.35 and 14.67, respectively, while the average governance performance score is 67.09, indicating a significant performance gap between different dimensions, with Chinese listed companies performing much better in governance than in environmental and social performance. The average Huazheng ESG rating is 4.398, indicating ESG's average rating between B and BB. The distributions of other financial and corporate governance variables fall within reasonable ranges.

Model design

Two-way fixed-effects model regressions can effectively control for the effects of year- and firm-related unobservable variables, reduce potential estimation bias, and improve the statistical reliability of regression results [120; 121]. Firms' ESG performance is not only strongly related to industry characteristics [122], but also affected by internal factors such as corporate culture [123], which are often difficult to observe directly but can systematically bias the results. Therefore, this study used a two-way fixed effects model to provide robustness and credibility to the results.

To test the correlation of AI and ESG, a regression model (1) was constructed.

$$ESG_{i,t} = \alpha_0 + \alpha_1 AI_{i,t} + \alpha_2 Controls_{i,t} + \sum Year + \sum Firm + \varepsilon_{i,t}. \quad (1)$$

Here, subscript i denotes the firm, t represents time, $ESG_{i,t}$ indicates the performance of ESG of firm i at year t, and $AI_{i,t}$ indicates the level of Artificial Intelligence of firm i at year t. $Controls_{i,t}$ indicates a set of control variables, $\sum Year$ and $\sum Ind$ represent the time fixed effects and firm fixed effects of the firm. $\varepsilon_{i,t}$ is the exogenous disturbance term, which follows a normal distribution with mean 0 and variance σ^2. According to the theoretical analysis, the coefficient α_1 of $AI_{i,t}$ is expected to be significantly positive because AI improves firms' ESG performance.

To validate the moderating effects of Inv_Att and ER on the correlation of AI and ESG, our research constructs models (2) and (3), drawing on the moderating effect model [124; 125].

$$ESG_{i,t} = \beta_0 + \beta_1 AI_{i,t} + \beta_2 Inv\_Att_{i,t} + \beta_3 Inv\_Att_{i,t} \times AI_{i,t} + \beta_4 Controls_{i,t} + \sum Year + \sum Ind + \varepsilon_{i,t}; \quad (2)$$

$$ESG_{i,t} = \gamma_0 + \gamma_1 AI_{i,t} + \gamma_2 ER_{i,t} + \gamma_3 ER_{i,t} \times AI_{i,t} + \gamma_4 Controls_{i,t} + \sum Year + \sum Ind + \varepsilon_{i,t}. \quad (3)$$

Here, $Inv\_Att_{i,t} \times AI_{i,t}$ and $ER_{i,t} \times AI_{i,t}$ are the interaction terms. If they are significant, it means that the moderating effect exists. According to the theoretical analysis, the coefficients β_3 and γ_3 are expected to be significantly positive.

Results and discussion

Correlation analysis

Table 4 presents the pairwise Pearson correlations among ESG performance, AI adoption, firm characteristics, and corporate governance variables. ESG is positively and significantly associated with AI adoption (r = 0.1805***), firm size (r = 0.4454***), leverage (r = 0.1335***), board independence (r = 0.0331***), and board size (r = 0.1143***), indicating that technologically advanced, larger, and well-governed firms tend to achieve better ESG performance. Conversely, ESG performance is negatively associated with environmental regulation (r = –0.3419***), firm age (r = –0.5642***), and Tobin's Q (r = –0.0386***). These results suggest that firms subject to stricter regulations, older firms, and those with higher market valuations tend to exhibit weaker ESG performance, possibly due to legacy constraints, lower adaptability, or different strategic priorities. All correlation coefficients remain below the conventional threshold of 0.8, with most well below 0.5, indicating that multicollinearity is unlikely to bias the regression analyses that follow.

Additionally, we calculated the variance inflation factors (VIFs) and found that the highest VIF value among the variables is 2.47, with an average VIF value of 1.55, both lower than the threshold of 10. Thus, multicollinearity does not appear to be an issue in this section of the study.

Table 4. Correlation matrix

	ESG	Environment	Social	Governance	Inv_Att	ER	AI	Size	Age	Lev	ROA	Growth	TobinQ	Boa_Dir	Ind	Top1	CEO_duality
ESG	1																
Environment	0.6532***	1															
Social	0.7600***	0.5418***	1														
Governance	0.6652***	0.3710***	0.3069***	1													
Inv_Att	0.1533***	0.0976***	0.1371***	0.0966***	1												
ER	-0.3419***	-0.2069***	-0.2437***	-0.2464***	-0.1222***	1											
AI	0.1805***	0.0864***	0.1460***	0.1774***	0.1045***	-0.0890***	1										
Size	0.4454***	0.3085***	0.3513***	0.3121***	0.3782***	-0.1344***	0.1304***	1									
Age	-0.5642***	-0.3775***	-0.3618***	-0.4506***	0.0658***	0.6737***	-0.2354***	-0.2162***	1								
Lev	0.1335***	0.0594***	0.0895***	0.1090***	0.1555***	-0.0284***	-0.0067	0.5801***	-0.0244**	1							
ROA	0.0128	0.0426***	0.0250**	-0.0242**	-0.0178*	0.0227**	0.012	-0.1221***	0.0112	-0.2928***	1						
Growth	-0.0049	0.0166	-0.0155	0.0059	-0.0114	0.0095	0.0013	0.0092	0.0067	0.0042	0.0025	1					
TobinQ	-0.0386***	-0.007	-0.0278***	-0.0313***	0.0088	0.0264**	0.0299***	-0.2631***	0.0218**	-0.2662***	0.7436***	-0.0041	1				
Boa_Dir	0.1143***	0.0647***	0.1195***	0.0610***	0.1686***	-0.0021	-0.0174	0.3400***	0.0342***	0.2179***	-0.0655***	-0.0112	-0.1040***	1			
Ind	0.0331***	0.0266**	0.0221**	0.0390***	0.0333***	-0.0499***	0.0481***	0.0277***	-0.0445***	-0.0153	0.0280***	0.0096	0.0362***	-0.3849***	1		
Top1	0.0128	0.0211**	0.0042	-0.0159	-0.0979***	0.0102	-0.1591***	0.0910***	0.0778***	0.0327***	0.0288***	-0.0115	-0.0566***	-0.0299***	0.0486***	1	
CEO_duality	-0.0145	-0.0077	-0.0059	-0.0163	-0.0094	0.0383***	-0.0084	-0.0376***	0.0247**	-0.0294***	0.0107	-0.007	0.0049	-0.0293***	-0.0007	-0.0106	1

Main effect regression analysis

Table 5 presents that AI has a significantly positive effect on overall ESG performance as well as its individual dimension at the 1% significance level, indicating that AI could improve ESG performance. In contrast, the positive impact on social performance is more modest, with a 0.802 increase. These findings suggest that AI is particularly effective in reducing corporate energy consumption, lowering emissions, optimizing green production management, and improving governance efficiency and transparency. However, in the social dimension, while AI contributes to improving working conditions, customer satisfaction, and product safety, the challenges it poses, like job displacement, privacy concerns, human rights violations, and other social inequalities, partially offset the positive effect of AI on the social dimension.

The regression results in Table 5 demonstrate that AI significantly enhances overall ESG performance and its subdimensions (Environmental, Social, and Governance), with all coefficients being positive and statistically significant at the 1% level, confirming Hypotheses 1–4. Firm size and market valuation (Tobin's Q) also exhibit strong positive effects on ESG outcomes, particularly in the Environmental and Social dimensions, while firm age and leverage show significant negative impacts, indicating that older and more leveraged firms tend to underperform in ESG.

Table 5. Main effect regression analysis

	Main effect regression				Robustness test
	ESG	Environmental	Social	Governance	ESG_hz
AI	0.851*** (3.42)	1.092*** (2.75)	0.802*** (3.16)	1.054*** (2.77)	0.011** (2.02)
Size	2.676*** (8.99)	3.339*** (7.33)	2.859*** (9.93)	0.321 (0.79)	0.063*** (13.62)
Age	−9.601*** (−35.08)	−9.358*** (−21.36)	−4.090*** (−14.48)	−14.502*** (−35.05)	0.057*** (10.54)
Lev	−6.714*** (−5.81)	−6.499*** (−3.82)	−5.959*** (−5.34)	−7.246*** (−4.02)	−0.186*** (−9.11)
ROA	0.037 (1.44)	0.040 (1.08)	0.020 (0.76)	−0.030 (−0.80)	−0.001*** (−2.99)
Growth	−0.108 (-1.17)	0.173 (1.09)	−0.141 (−1.59)	0.022 (0.16)	−0.003 (−1.29)
TobinQ	0.411*** (4.76)	0.506*** (3.77)	0.435*** (4.81)	0.178 (1.54)	0.006*** (3.01)
Boa_Dir	0.088 (0.83)	0.196 (1.19)	0.010 (0.09)	0.124 (0.76)	−0.002 (−0.95)
Ind	0.050** (2.10)	0.088** (2.27)	0.040* (1.72)	0.031 (0.82)	0.002*** (3.83)
Top1	0.055*** (3.04)	0.046* (1.79)	0.048*** (2.75)	0.052** (2.26)	−0.000 (−0.59)
CEO_duality	0.263 (1.26)	0.195 (0.60)	0.146 (0.68)	−0.032 (−0.09)	0.018*** (4.06)
Constant	−19.386*** (−2.72)	−54.754*** (−5.05)	−45.921*** (−6.62)	76.500*** (7.89)	−2.813*** (−5.23)
Year FE	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Observations	8.906	8.906	8.906	8.906	8.906
R^2–within	0.561	0.399	0.313	0.420	0.045
R^2–between	0.458	0.200	0.159	0.377	0.101
R^2–overall	0.465	0.295	0.230	0.347	0.080

Note: The T statistic is in parentheses; *, **, and *** represent 10%, 5%, and 1% significance levels, respectively.

Robustness test

Based on previous studies [107; 126], this section of the study replaces ESG with ESG_hz in the baseline regression model to verify the robustness of our research. The results in Table 5 indicate that the estimated coefficient of AI level on ESG_hz is significantly positive at the 5% level, indicating that the study's conclusions remain robust.

Moderating effect of investor attention

Table 6 presents the results of the moderating effect of investor attention. The interaction term (AI×Inv_Att) is significantly positive for overall ESG performance ($\beta_3 = 0.574$, $p < 0.01$) and its three sub-dimensions, suggesting that investor attention significantly strengthens the positive correlation between AI adoption and ESG outcomes.

However, a more nuanced picture emerges when observing the direct effect of AI. Upon including the interaction term, the main effect coefficient of AI becomes significantly negative ($\beta_1 = -3.258$, $p < 0.05$). This negative baseline coefficient indicates that when investor attention is absent or at an extremely low level, AI adoption may actually exert a detrimental impact on corporate ESG performance. By calculating the inflection point ($-\beta_1/\beta_3$), we find that the impact of AI on ESG only turns positive when investor attention exceeds the threshold of 5.68. Similarly, the specific thresholds for the Environmental, Social, and Governance dimensions are 6.07, 5.94, and 5.53, respectively.

This finding uncovers a critical digitalization paradox in corporate sustainability [38]. Without sufficient external soft regulation, the deployment of AI often serves as a tool for narrow profit maximization rather than holistic value creation. From an environmental perspective, the substantial energy footprint and resource intensity required to maintain AI infrastructure can lead to a rebound effect, where technological efficiency gains are eclipsed by increased ecological burdens [51]. In the social dimension, in the absence of public scrutiny, firms are more likely to implement the "wrong kind of AI" – prioritizing labor-displacing automation over task-enhancing innovation, which adversely affects employee welfare and social equity [127]. Furthermore, the high initial costs of AI may trigger managerial myopia, leading firms to redistribute resources away from long-term ESG initiatives to offset technological expenses.

In summary, investor attention, measured by the Baidu Index, functions as a vital informal governance mechanism. It creates a reputational pressure that compels management to move beyond the efficiency-only paradigm. High levels of public scrutiny incentivize firms to leverage AI's precision for green innovation and transparent governance, effectively transforming AI from a potential sustainability risk into a powerful driver of corporate ESG transformation.

Table 6. Moderating effect of investor attention

	ESG	Environmental	Social	Governance
AI	−3.258** (−2.10)	−6.071*** (−2.84)	−3.898** (−2.45)	−3.565* (−1.79)
Inv_Att	−0.113 (−0.42)	−0.378 (−1.07)	−0.456* (−1.91)	−0.423 (−1.61)
AI × Inv_Att	0.574*** (2.66)	1.000*** (3.32)	0.656*** (2.94)	0.645** (2.38)
Size	2.674*** (8.91)	3.370*** (7.33)	2.920*** (9.99)	0.376 (0.92)
Age	−9.544*** (−34.74)	−9.285*** (−21.13)	−4.070*** (−14.38)	−14.479*** (−34.78)
Lev	−6.744*** (−5.85)	−6.531*** (−3.85)	−5.956*** (−5.35)	−7.247*** (−4.02)
ROA	0.037 (1.43)	0.040 (1.09)	0.021 (0.79)	−0.029 (−0.78)
Growth	−0.110 (−1.19)	0.167 (1.05)	−0.148* (-1.66)	0.015 (0.11)

	ESG	Environmental	Social	Governance
TobinQ	0.403*** (4.65)	0.501*** (3.72)	0.442*** (4.86)	0.183 (1.57)
Boa_Dir	0.096 (0.92)	0.210 (1.28)	0.018 (0.17)	0.132 (0.81)
Ind	0.050** (2.13)	0.090** (2.31)	0.041* (1.78)	0.032 (0.85)
Top1	0.054*** (2.99)	0.044* (1.71)	0.045*** (2.58)	0.049** (2.15)
CEO_duality	0.261 (1.25)	0.191 (0.59)	0.144 (0.67)	–0.035 (–0.10)
Constant	–18.720*** (–2.61)	–53.035*** (–4.88)	–44.155*** (–6.31)	78.156*** (8.00)
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Observations	8.906	8.906	8.906	8.906
R^2–within	0.562	0.399	0.314	0.421
R^2–between	0.456	0.195	0.159	0.379
R^2–overall	0.466	0.294	0.230	0.348

Note: The T statistic is in parentheses; *, **, and *** represent 10%, 5%, and 1% significance levels, respectively.

Moderating effect of environmental regulation

Table 7 shows that government environmental regulation positively moderates the relationship between AI and overall ESG performance, as well as between AI and environmental and governance performance. However, it has no significant moderating effect on the relationship between AI and social performance. This could be because stringent environmental regulation increases corporate investment in environmental management, leading to a focus on AI application in environmental management while reducing attention to social responsibility, which partly confirms the findings of Yan et al. [93]. However, unlike the results of that research, our results show that stricter environmental regulations also encourage greater AI adoption in corporate governance. This divergence can be attributed to the critical role of compliance and transparent governance in addressing the scrutiny and accountability demands posed by external regulatory bodies. Effective governance frameworks can enhance a firm's ability to comply with regulatory standards, mitigating risks associated with environmental regulation and supporting more robust and informed environment-related decision-making [128–130].

Table 7. Moderating effect of environmental regulation

	ESG	Environmental	Social	Governance
AI	0.051 (0.11)	−0.475 (−0.68)	0.855 (1.58)	0.266 (0.55)
ER	0.034 (0.33)	−0.113 (−0.81)	0.230* (1.94)	−0.182 (−1.18)
AI×ER	0.087** (2.06)	0.171*** (2.89)	−0.011 (−0.23)	0.088** (2.13)
Size	2.681*** (9.04)	3.427*** (7.59)	2.912*** (10.14)	0.324 (0.79)
Age	−10.031*** (−14.89)	−9.102*** (−9.58)	−5.383*** (−6.92)	−13.659*** (−13.50)
Lev	−7.641*** (−6.61)	−7.444*** (−4.37)	−6.976*** (−6.23)	−7.384*** (−4.07)
ROA	−0.029* (−1.93)	−0.038* (−1.74)	−0.034** (−2.25)	−0.042** (−2.35)
Growth	0.000*** (3.65)	0.000*** (8.94)	0.000 (1.20)	0.000*** (7.47)
TobinQ	0.130** (2.12)	0.232** (2.51)	0.173*** (2.72)	0.095 (1.44)
Boa_Dir	0.099 (0.94)	0.201 (1.23)	0.017 (0.17)	0.127 (0.78)
Ind	0.053** (2.23)	0.091** (2.32)	0.043* (1.83)	0.032 (0.85)
Top1	0.054*** (2.97)	0.046* (1.79)	0.048*** (2.76)	0.051** (2.22)
CEO_duality	0.301 (1.43)	0.253 (0.78)	0.168 (0.78)	−0.008 (−0.02)
Constant	−17.661** (−2.49)	−54.860*** (−5.08)	−45.321*** (−6.56)	76.540*** (7.81)
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Observations	8.906	8.906	8.906	8.906
R2 – within	0.560	0.398	0.312	0.421
R2 – between	0.459	0.199	0.158	0.383
R2 – overall	0.465	0.295	0.229	0.348

Note: The T statistic is in parentheses; *, **, and *** represent significance levels of 10%, 5%, and 1%, respectively.

Endogeneity test

Although the two-way fixed effects model reduces estimation bias, endogeneity issues may still persist, particularly due to potential unobserved variables or omitted variable bias between AI and ESG performance. To mitigate these potential endogeneity problems, this study introduces the lagged Digital Economy Index (DEI_{t-1}) at the city level and the lagged AI application level (AI_{t-1}) as instrumental variables, using a two-stage least squares (2SLS) regression. The DEI is calculated using the approach proposed by Tao et al. [131] based on data from the China City Statistical Yearbook and the Local Statistical Yearbooks for cities at the prefecture level and above.

The rationale for selecting these two instrumental variables (DEI_{t-1} and AI_{t-1}) is as follows: First, the level of AI adoption within a firm is closely linked to the level of digital development in the region where the firm operates. The relevant literature suggests that when other firms in the same region experience rapid digital economic growth, the likelihood and extent of digital technology adoption by an individual firm also increase [132]. Therefore, DEI_{t-1} satisfies the relevance condition through technological spillovers. Second, AI_{t-1} strongly predicts current AI usage due to technological path dependency.

To ensure the validity of the exclusion restriction, we provide a multi-layered justification. A potential concern is that regional digital infrastructure (DEI_{t-1}) might influence firm-level ESG through alternative channels like human capital aggregation or improved access to green technologies. We mitigate these concerns, first, through a "channel blocking" effect, whereby these alternative pathways are largely internalized by our extensive control variables (e.g., firm size and governance) and firm-year fixed effects, which absorb macro-level technological and regulatory shocks. Second, we argue that AI serves as the essential "downstream execution" mechanism; while a city's digital ecosystem provides the external opportunity, the actual translation of infrastructure into improved ESG outcomes–such as real-time carbon tracking–requires the strategic deployment of AI within the firm [133].

Regarding the exclusion restriction of AI_{t-1}, we argue that potential persistent effects from past technological adoption do not systematically bias our estimates for two reasons.

First, the control of Firm Fixed Effects. By incorporating firm-level fixed effects, our model effectively absorbs time-invariant firm-specific characteristics, including the firm's baseline technological level. Consequently, the regression identifies the impact of incremental changes in AI strategic intensity on ESG improvements, rather than level-based persistence.

Second, the Transmission Mechanism through Current Adoption. In line with technological path-dependency, the influence of AI_{t-1} on current ESG performance is predominantly manifested through its high correlation with current-year AI strategic prioritization (AI_t). Therefore, the 'direct' impact of past adoption is largely internalized by the endogenous regressor itself.

Empirically, our instrumental variable strategy is supported by robust diagnostic statistics. In Table 8, the coefficients of DEI_{t-1} and AI_{t-1} are significant at the 5% and 1% levels, respectively, indicating a strong correlation between the instrumental variables and AI. In Column (3), the Kleibergen-Paap rk LM statistic shows a p-value below 0.01, rejecting the null hypothesis of "under-identification of instrumental variables." Both the Cragg-Donald Wald F statistic and the Kleibergen-Paap rk Wald F statistic exceed the critical threshold at the 10% level (19.93), indicating no issue of weak instrumental variables. Furthermore, the p-values for both the Hansen J-test and Sargan test were greater than 0.1, confirming no over-identification concerns. In the second stage, AI's coefficient remains significantly positive at the 1% level (2.059), indicating that AI continues to have a substantial positive impact on ESG performance, and this effect is larger after accounting for endogeneity compared to the ordinary least squares results.

Table 8. Endogeneity test

	First stage		Second stage
	AI	AI	ESG
AI			2.059*** (2.59)
DEI_{t-1}	0.013** (2.04)		
AI_{t-1}		0.254*** (20.51)	
Size	0.095*** (7.58)	0.075*** (6.18)	2.647*** (10.56)

	First stage		Second stage
	AI	AI	ESG
Age	−0.156*** (−12.76)	−0.107*** (−8.90)	−4.148*** (−6.20)
Lev	−0.104* (−1.95)	−0.087* (−1.68)	−5.237*** (−5.77)
ROA	−0.001 (−1.44)	−0.001 (−0.78)	0.022* (1.41)
Growth	−0.004 (−0.63)	−0.003 (−0.63)	−0.100 (−1.26)
TobinQ	0.001 (0.20)	0.002 (0.38)	0.334*** (4.49)
Boa_Dir	0.001 (0.18)	−0.001 (−0.20)	0.137* (1.76)
Ind	0.001 (0.81)	0.001 (0.58)	0.058*** (3.04)
Top1	−0.002*** (−3.12)	−0.002** (−2.11)	0.031** (2.45)
CEO_duality	0.013 (1.28)	0.012 (1.22)	0.204 (1.24)
Constant	−1.515*** (−4.99)	−1.176*** (−4.01)	−19.507*** (−3.94)
Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Observations	7.221	7.221	7.221
R^2–within	0.147	0.202	0.594
R^2–between	0.039	0.612	0.472
R^2–overall	0.059	0.467	0.459
Kleibergen-Paap rk LM statistic			233.293[0.000]
Kleibergen-Paap rk Wald F statistic			129.469
Cragg-Donald Wald F statistic			212.113
Sargan test			0.686[0.4076]
Hansen J test			0.624[0.4294]

Note: The T statistic is in parentheses; *. **. and *** represent 10%. 5%. and 1% significance levels. respectively; the P value is in brackets.

Heterogeneity analysis

The impact of AI on ESG performance may vary depending on a firm's ownership structure, which dictates its strategic priorities, resource allocation logic, and institutional environment. To explore this, we categorize the sample into state-owned enterprises (SOEs) and non-state-owned enterprises (non-SOEs). As shown in Table 9, while AI significantly promotes overall ESG performance in both groups, a distinct "functional specialization" emerges: AI primarily drives environmental (E) performance in SOEs, whereas its facilitative effect is concentrated on social (S) and governance (G) performance in non-SOEs.

This divergence is rooted in the different institutional logics and AI application scenarios in these two types of firms.

First, for SOEs, the impact of AI is heavily shaped by coercive isomorphism– the pressure to align with national strategic mandates [134]. Under China's "Double Carbon" goals, environmental performance is not merely a social responsibility but a key political KPI for SOE executives. Given that SOEs are predominantly concentrated in asset-heavy, high-polluting industries (e.g., energy, chemicals, and heavy manufacturing), they are more likely to adopt "Industrial AI" and "Hard Tech" solutions. These include IoT-based real-time emission monitoring, predictive maintenance for energy-intensive equipment, and AI-driven industrial process optimization. Such technologies yield direct, quantifiable improvements in energy efficiency and pollution control, explaining why AI's impact is most pronounced in the environmental dimension for SOEs. While SOEs possess the resources to improve S and G, their baseline in these areas is already high due to standardized administrative structures and state oversight, leading to a diminishing marginal utility of AI for incremental social or governance gains.

Second, for non-SOEs, the primary driver is market signaling and competitive advantage. Non-SOEs often operate in more competitive, consumer-facing, or asset-light sectors where brand reputation and investor trust are paramount. Consequently, their AI investments tend to gravitate toward "Administrative AI" and "Management Soft Tech". This includes AI-driven supply chain transparency tools, data analytics for enhancing employee welfare and customer satisfaction (S), and blockchain-based internal audit or digital transparency systems (G). These applications are designed to signal "high-quality governance" to capital markets and reduce information asymmetry for external investors. Furthermore, non-SOEs have more flexible organizational structures, allowing AI to more effectively streamline decision-making processes and enhance governance agility compared to the more rigid, multi-layered hierarchies of SOEs.

Third, differences in reporting and operational practices create distinct statistical patterns. SOEs are subject to rigorous, top-down environmental audits and standardized reporting systems, making the environmental benefits of AI more visible and accurately captured in ESG ratings. In contrast, non-SOEs often leverage digital transformation as a "legitimacy tool" to attract ESG-conscious investors. By adopting AI in governance and social programs, they can provide more robust and transparent data to rating agencies, leading to significant improvements in their S and G scores.

In conclusion, our results demonstrate that AI is not a universal panacea but a strategic tool whose impact is mediated by ownership-specific technological affordances and strategic imperatives. AI helps SOEs fulfill their role as environmental stewards through industrial optimization, while it assists non-SOEs in building market legitimacy through management and stakeholder engagement.

Conclusion and discussion

Corporate sustainability is a key driver of national economic progress and global competitiveness, shaping both domestic growth trajectories and international perceptions. As the global economy undergoes a transformative shift toward sustainable and inclusive growth, Artificial Intelligence (AI) has emerged as a GPT that functions as a systemic catalyst for innovation, efficiency, and long-term value creation. This study offers a comprehensive exploration of AI's impact on ESG performance by utilizing an aggregate index of digital intelligence intensity.

In contrast to prior research that emphasizes AI's impact on economic benefits [20] or its macro-level societal implications [19], this paper contributes to the literature by demonstrating that AI's impact is a systemic phenomenon that permeates internal operations, supply chains, and societal interactions. This framework breaks away from the limited or isolated discussions of AI and ESG in existing literature and expands on Babina's work [135] on AI-driven corporate growth by providing new theoretical insights into AI's complex role in sustainable corporate development.

Our findings reveal that AI significantly promotes overall ESG performance, with the most pronounced effects on the environmental and governance dimensions. This is driven by an "innovation compensation effect", where technological efficiencies in resource optimization and decision-making outweigh the inherent costs of implementation. However, the social impact remains nuanced; while AI enhances workplace safety and supply chain transparency, these gains are partially offset by concerns regarding labor displacement and algorithmic bias. These results underscore that AI is not a universal panacea but a strategic tool that requires careful alignment with ethical norms.

A primary contribution of this study is uncovering the non-linear, threshold-based moderating role of investor attention. We demonstrate the existence of a "digitalization paradox" [38; 39]: at low levels of public scrutiny, AI adoption can inadvertently harm ESG performance as firms may prioritize short-term operational efficiency over sustainability. The facilitative effect of AI only emerges once investor attention surpasses a critical threshold, highlighting the indispensable role of external "soft" regulation in ensuring that technological gains do not come at the cost of social

Table 9. Heterogeneity analysis

	Non-SOEs				SOEs			
	ESG	Environmental	Social	Governance	ESG	Environmental	Social	Governance
AI	0.972***	0.640	1.160***	1.368**	0.614**	1.259***	0.331	0.599
	(2.73)	(1.08)	(3.34)	(2.25)	(2.53)	(2.58)	(1.33)	(1.21)
Size	3.840***	4.407***	3.901***	1.480***	1.986***	2.612***	2.486***	0.124
	(13.23)	(9.10)	(13.79)	(2.98)	(9.25)	(6.05)	(11.24)	(0.28)
Age	–7.713***	–8.472***	–1.888***	–11.765***	–10.553***	–9.762***	–5.213***	–15.632***
	(–20.94)	(-13.79)	(–5.26)	(–18.68)	(–46.37)	(–21.32)	(–22.24)	(–33.63)
Lev	–7.869***	–8.364***	–7.122***	–6.310***	–5.446***	–5.461***	–4.301***	–4.997***
	(–6.31)	(–4.02)	(–5.86)	(–2.96)	(–5.81)	(–2.90)	(–4.45)	(–2.61)
ROA	0.026	0.018	0.011	–0.067*	–0.024	–0.023	–0.022	––0.025
	(1.21)	(0.50)	(0.51)	(–1.85)	(–1.60)	(–0.75)	(–1.40)	(–0.81)
Growth	–0.003	0.000	–0.002	0.000	0.000	0.000	–0.000	0.000
	(–0.55)	(0.02)	(–0.47)	(0.06)	(0.35)	(1.21)	(–0.09)	(0.92)
Tobin Q	0.376***	0.501***	0.445***	0.240*	0.057	0.112	0.077	0.035
	(4.76)	(3.81)	(5.79)	(1.77)	(0.97)	(0.95)	(1.27)	(0.29)
Boa_Dir	0.048	0.343	–0.004	–0.072	0.122	0.148	0.014	0.184
	(0.32)	(1.35)	(–0.03)	(–0.28)	(1.54)	(0.93)	(0.18)	(1.14)
Ind	0.066*	0.105	0.067*	–0.045	0.047**	0.087**	0.028	0.052
	(1.66)	(1.59)	(1.73)	(–0.66)	(2.37)	(2.16)	(1.38)	(1.26)
Top1	0.075***	0.098***	0.057***	0.073**	0.031**	0.018	0.021*	0.007
	(3.85)	(2.99)	(2.96)	(2.17)	(2.48)	(0.71)	(1.69)	(0.29)
CEO_duality	–0.172	0.000	–0.403	–0.236	0.647***	0.351	0.742***	0.125
	(–0.63)	(0.00)	(–1.52)	(–0.51)	(3.16)	(0.85)	(3.52)	(0.30)
Constant	–48.653***	–81.346***	–73.070***	48.877***	–1.000	–36.151***	–34.537***	83.009***
	(–6.82)	(–6.84)	(–10.51)	(4.01)	(–0.20)	(–3.53)	(–6.58)	(7.98)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3.949	3.949	3.949	3.949	4.957	4.957	4.957	4.957
R-squared	0.486	0.397	0.272	0.315	0.655	0.407	0.395	0.509

Note: The T statistic is in parentheses; *. **. and *** represent significance levels of 10%. 5%. and 1%. respectively.

and environmental integrity. Regarding environmental regulation, the findings show that AI's contributions to environmental and governance performance are more pronounced when environmental regulation is stricter. Meanwhile, non-significant moderation of the social dimension points to a potential 'resource crowding-out' effect: under rigid administrative mandates, firms are incentivized to prioritize legally sensitive environmental and governance goals, which may inadvertently sideline voluntary social responsibilities due to finite resource allocation [93].

Furthermore, our research provides novel insights into the heterogeneity of AI impact across institutional logics. We find a distinct "functional specialization": SOEs leverage AI primarily to improve environmental performance, driven by coercive isomorphism and national strategic mandates like China's "Double Carbon" goals. In these firms, AI is channeled into "industrial solutions" for emission control. Conversely, non-SOEs utilize AI as a signaling mechanism to improve social responsibility and governance transparency, aiming to build market legitimacy and attract ESG-conscious investors. These distinctions suggest that the transformative power of AI is contingent upon the firm's ownership-specific strategic imperatives and application scenarios.

In conclusion, this study underscores the transformative potential of AI while identifying the critical roles of external monitoring and ownership structures in maximizing its benefits. As AI technologies continue to evolve, their integration into corporate ESG strategies will require a delicate balance between efficiency and ethics, supported by robust regulatory frameworks. This research offers valuable guidance for policymakers and managers, emphasizing that the path to AI-driven sustainability is not automatic but requires active oversight and strategic tailoring to institutional environments.

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