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AI and Data Technologies in Advancing ESG Performance Goals: A Moderated Mediation Model

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Abstract. With the rapid development of computer science, especially artificial intelligence (AI) and big data analysis, human thinking is changing dramatically. AI's data processing, pattern recognition, automated decision making and machine learning capabilities are reshaping business models and impacting industries. Big data is an important factor in enabling companies to achieve high performance and make in-formed decisions. In China's A-share market, many companies are adopting AI for digital transformation and improving aspects such as their environmental, social and governance (ESG) performance. This article uses Python and big data techniques to analyze the AI-related terms of these companies and assess their digital development. Our ordinary least squares (OLS) regression analysis using Stata revealed three key findings: AI significantly improves ESG performance; Green innovation plays an intermediary role in this relationship; this effect is mitigated by the degree of ownership concentration, and the higher the degree of ownership concentration, the greater the effect. This study contributes to under-standing the role of AI in sustainable development and provides recommendations for using AI and big data to improve ESG performance.

Keywords: artificial intelligence technology, big data analysis technology, environmental, social and governance performance, green technology innovation, ownership concentration

1 Introduction

With the rapid development of artificial intelligence (AI) and big data analysis, the global economy and society are undergoing profound transformations. AI, with its powerful data processing, pattern recognition, and automated decision-making capabilities, is helping various industries optimize business processes and innovate business models [1]. In particular, AI's potential in the field of sustainable development cannot be overlooked [2]. In the Chinese A-share market, an increasing number of companies are driving digital transformation through AI and making progress in their environmental, social, and governance (ESG) performance [3]. However, research on how AI enhances corporate ESG performance and its specific mechanisms is still in its early stages.

The application of AI technology in corporate management and the ESG field has significant practical relevance. By processing and analyzing large volumes of data, AI can assist companies in making smarter decisions in environmental protection, social responsibility, and corporate governance, helping them achieve sustainable development goals [3]. At the same time, AI can promote green innovation, driving companies to make advances in environmental technology and energy conservation, thus creating long-term competitive advantages [4]. Therefore, studying how AI affects corporate ESG performance holds both theoretical and practical significance.

As global attention to sustainable development grows, the relationship between AI and corporate ESG per-

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formance has gradually become a research hotspot in both academia and practice. Existing studies have already achieved many results regarding the role of AI in corporate management, innovation, and operational efficiency. However, there is still a research gap in how AI specifically improves corporate ESG performance. In studies on AI and corporate performance, many scholars have found that AI can enhance overall corporate performance by improving operational efficiency, reducing resource waste, and optimising supply chain management. For example, Agrawal et al. [5] pointed out that AI's powerful capabilities in data processing and automated decision-making can significantly enhance corporate efficiency and in-novation. Furthermore, AI applications can help companies improve environmental management and promote green innovation. For instance, Chen et al. [3] found that AI, through technological innovation, helps companies achieve better performance in green production and sustainable development.

However, research on the specific impact of AI on ESG, especially integrative studies covering the environmental, social, and governance dimensions, remains relatively scarce. Some studies have started exploring the role of AI in environmental management, such as how AI-based energy-saving technologies and pollution monitoring systems contribute to reducing corporate environmental pollution. Nevertheless, studies on AI's role in social responsibility and governance are still insufficient. Hohma et al. [6] suggested that AI can improve governance transparency and risk management, thereby enhancing corporate governance and optimizing corporate social responsibility performance. Despite this, the mechanism by which AI influences corporate performance under different ownership structures remains an area with significant research potential. Existing research tends to focus on overall corporate performance, neglecting AI's differential impact in governance structures such as ownership concentration.

In addition, green innovation as an important mediating mechanism has received increasing attention in recent years. Studies have shown that AI promotes corporate technological innovation, particularly in the application of green technologies [4, 7], which can play a key role in enhancing ESG performance. While these studies have laid a foundation for understanding the relationship between AI and corporate ESG, most have not systematically revealed the interactions between AI, green innovation, and ESG.

Therefore, there is still substantial room for improvement in the integrative analysis of AI and ESG performance in current research, especially regarding how AI, through green innovation, influences corporate ESG performance under different ownership structures. Systematic empirical studies are lacking in this area. Based on data from the Chinese A-share market, this paper uses Python and big data technology to analyze AI-related corporate information and employs ordinary least squares (OLS) regression models to systematically assess the impact of AI on corporate ESG performance. The main contributions of this paper are as follows: First, it provides the first empirical analysis of the relationship between AI and corporate ESG performance, offering new perspectives on AI's role in sustainable development. Second, it reveals the mediating role of green innovation in the relationship between AI and ESG performance. Finally, it explores how ownership concentration moderates the impact of AI on ESG performance, enriching research on AI and corporate governance.

Through these studies, this paper not only deepens the understanding of AI's role in corporate sustain-able development but also provides valuable strategic recommendations for companies to effectively lever-age AI and big data technologies to improve ESG performance.

2 Literature Review and Hypothesis Development

2.1 AI Technology

Artificial intelligence includes technology that simulates human intelligence through computer programs. It enables computers to perform complex tasks such as personal perception, inference, and learning by simulating human abilities [8, 9]. Core algorithms such as machine learning and deep learning allow AI to recognize patterns and perform operations such as classification and prediction [10, 11]. Artificial intelligence is a branch of computer science that includes fields such as robotics, speech recognition, animation recognition, natural human language processing, and experts.

AI research has been evolving for decades, beginning with a formal research program at Dartmouth College in the 1950s [12]. Early symbolic methods aimed to simulate intelligence through logical reasoning but faced difficulties due to limited computational power [12]. In the late 1970s, expert systems emerged and applied artificial intelligence to solve specific problems in daily life by imitating people's professional knowledge [13]. The late 1990s marked the shift to machine learning, utilizing algorithms to improve performance through data-driven learning [14]. Deep learning, a branch of machine learning, simulates neural networks, achieving breakthroughs in computer vision, natural language processing, and speech recognition [14]. Today, AI is expanding into fields like healthcare, finance, and manufacturing, with emerging technologies such as reinforcement learning and generative AI gaining prominence. As AI continues to drive innovation, it also raises ethical and legal concerns. Overall, the trajectory of AI research reflects a progression from theoretical exploration to practical application and integration with other technologies.

2.2 AI Technology and ESG

The use of AI in enterprise management is rapidly growing. Companies are increasingly integrating AI to enhance efficiency and competitiveness [15, 16]. In human resources, AI automates recruitment processes, improving fairness and accuracy while reducing HR workload [17, 18]. In finance, AI provides automated data analysis and risk management solutions, helping companies optimize resource allocation and understand their financial status [19, 20]. AI plays a crucial role in supply chain management [21-23], Customer Service [24, 25], forecasting market demand [26, 27] and optimized inventory [28, 29]. Despite his benefits, challenges such as whether the algorithm is stable, the complex difficulty of data processing, the technology, and staff training remain [9, 30].

The use of AI in business management to improve environmental quality, social and governance (ESG) performance is increasing. Artificial intelligence supports ESG management by automatically collecting data from a variety of sources to create a unified view of ESG data [31, 32]. AI also facilitates risk assessment and rapid identification of potential ESG-related risks in order to mitigate losses in a timely manner [31, 32]. In addition, AI improves the efficiency of ESG reporting, produces reports that meet requirements, enhances transparency and credibility, and facilitates viewing with stakeholders [33, 34]. As technology advances, the role of AI in improving ESG performance will rise. Overall, AI is a key part of achieving sustainable development goals for businesses.

H1: AI positively affects corporate ESG performance.

2.3 Mediating Effect of Green Technology Innovation Played between AI and ESG

In the context of global warming and the increasing shortage of resources, how to achieve sustainable development of enterprises has become the focus of attention. ESG performance is an important indicator to measure the sustainable development ability of enterprises, and it is gradually receiving more and more enterprises' attention [35]. The rapid development of artificial intelligence technology has opened new ground for promoting green technology innovation within enterprises and improving ESG performance. [3, 36, 37].

Artificial intelligence technology, with its powerful data processing and analysis ability, for the enterprise of green technology innovation provides an important support [38, 39]. In the traditional green technology innovation method, enterprises are often faced with unpredictable market demand, difficulties in optimizing the production process, and low resource utilization efficiency. However, by integrating AI technology, enterprises can more accurately detect the changing position of market demand, and timely adjust product design and production strategies to meet consumers' preference for environmentally friendly products [38, 39]. In addition, AI technology can help enterprises optimize production processes, reduce energy consumption, and minimize waste emissions, resulting in greater resource efficiency and better overall environmental performance [20, 40].

While promoting green technology innovation, AI has a positive impact on firms' ESG performance [41]. First, in terms of environmental issues, artificial intelligence technology helps to reduce carbon emissions and environmental pollution by optimizing energy management and resource utilization [20]. This optimization helps companies achieve energy saving, emission reduction and sustainable production goals [20]. Secondly, from a social perspective, the application of AI technology improves the social image and brand value of enterprises [42]. By disclosing high-quality ESG reports that highlight a company's efforts and achievements in sustainability, organizations can strengthen the trust and goodwill of investors, consumers and the public, thereby enhancing their market competitiveness [43, 44]. Finally, in terms of corporate governance, artificial intelligence technology to the company's internal governance provides a more effective and more visualization method. Through the application of machine auditing and risk management, companies can strengthen the control of internal person and supervision, improve governance efficiency and transparency, and reduce risks

H2: Green technology innovation mediates the positive effect of AI on ESG performance.

2.4 The Moderating Effect of Ownership Concentration Played between AI and ESG

Ownership concentration is to evaluate executives inside ownership distribution and degree of big share-holder control of important terms, by using artificial intelligence technology to improve enterprise ESG performance has an important positive role. In highly centralized ownership structures, major shareholders or controlling shareholders have a greater influence on planning decisions, resource allocation and enterprise risk management within the company due to their larger equity [45]. When a company is committed to improving production processes through AI technology, improving energy efficiency, and improving ESG performance in order to reduce environmental pollution, this factor of high ownership concentration can have some positive effects. First, it speeds up decision making and minimizes the delays and internal coordination costs associated with decentralized equity. This efficiency enables companies to adopt and implement technological innovations to improve their ESG performance faster. Secondly, large shareholders tend to prioritize a company's long-term growth and socially responsible image, making them more inclined to invest in projects that provide both financial returns and improved environmental and social outcomes [46]. This tendency has led the company toward greener and more sustainable options in choosing AI techologies. Furthermore, the robust risk-bearing capacity of major shareholders offers essential financial support and psychological reassurance for the company to embrace new technologies and methods for ESG management. This support enables the company to maintain its strategic focus and continue investing, even when confronted with challenges such as high initial costs and extended return cycles. Hence, the following hypothesis is proposed:

H3: Ownership concentration moderates the positive effect of AI on ESG performance.

H4: Ownership concentration plays a moderated mediation effect between AI and ESG performance.

The theoretical model is shown in Fig. 1.

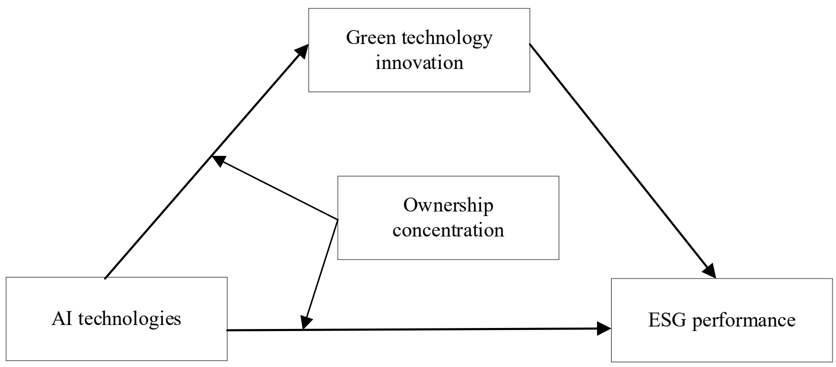

Fig. 1. Theoretical model

3 Methodology

3.1 Data Sources and Sample Selection

This study collects a dataset consisting of Chinese A-share listed companies from 2009 to 2022. The dataset consists of four sources. The annual reports are extracted from the CNINFO platform, and they are processed to analyse AI-related discourse. The ESG performance data is obtained from the Wind database, including ratings across the dimensions of Environment (E), Social (S) and Governance (G). Green technology innovation is the data extracted from the Wind database. It is focusing on green inventions and utility models. Finally, the firm-level attributes are the financial and governance data retrieved from the China Stock Market and Accounting Research (CSMAR) database. In accordance with the methodological standards, this study excludes firms under special treatment (ST/*ST), financial institutions, and companies with incomplete data. The continuous variables are winsorised at the 1% and 99% levels to mitigate the impact of extreme values. A final dataset of 37,120 firm-year observations is constructed.

To ensure the reliability of data, an automated anomaly detection framework is employed. The cross-database consistency is used to align the firm-level identifiers and key variables across CNINFO, Wind, and CSMAR databases. The document structure and encoding standardisation (UTF-8) is applied for metadata verification to handle the Chinese text and special characters.

3.2 Measurements of Variables

Artificial Intelligence (AI). The measurement of AI technology adoption in this study employs an approach that extends beyond the traditional keyword frequency analysis by incorporating advanced Natural Language Processing (NLP) and Machine Learning (ML) techniques, building upon foundational approaches outlined by Yao et al. [47]. Aligned with his research, this study evaluates AI technologies by employing word frequency statistics and text analysis of annual reports from various listed companies. Since there is no space partition between Chinese characters, words and expressions serve as the smallest language unit that can be used independently. Therefore, it is necessary to perform specialised word segmentation processing on the text of annual reports.

This study uses the Python open-source “jieba” Chinese word segmentation module to tokenise the text of listed companies’ annual reports. However, Chinese text analysis presents three primary challenges: segmentation granularity, ambiguous word recognition, and new word recognition. For instance, “machine learning” is often segmented into two separate terms, “machine” and “learning,” which dilutes its contextual meaning. To address this, following the approach of Yao et al. [47], a domain-specific AI dictionary is integrated as a preset lexicon into the segmentation module. This ensures that key AI terms, such as “machine learning” and “deep learning,” are correctly identified and treated as cohesive units.

In order to solve this problem, Yao et al. [47] added the generated AI dictionary (Fig. 2) as a preset lexicon of proper nouns into the word division module of “jieba”. Fig. 2 provides a visual representation of the AI dictionary used for segmentation, including specific examples of terms and phrases. By integrating this dictionary, the number of AI-related terms in the annual reports of listed companies was identified and quantified. Subsequently, the natural logarithm of the number of AI keywords plus one is used as the index of AI adoption for enterprises.

Beyond this traditional approach, this study extends the analysis by employing semantic embedding techniques to capture the contextual relationships of AI-related terms within the broader narrative of annual reports. Each segmented text is converted into high-dimensional vectors using the pre-trained Bidirectional Encoder Representations from Transformers (BERT) model on Chinese corpora. BERT embeddings provide a deeper understanding of how AI technologies are framed and contextualised within firms’ ESG strategies.

```
tokenizer = BertTokenizer.from_pretrained(“bert-base-chinese”)
model = BertModel.from_pretrained(“bert-base-chinese”)

def get_embedding(text):
    tokens = tokenizer(text, return_tensors=”pt”, padding=True, truncation=True)
    outputs = model(**tokens)
    return outputs.last_hidden_state.mean(dim=1).detach().numpy()

ai_sentence = “ Companies are applying deep learning to optimise processes “
esg_term = “Green Technology Innovation”

ai_embedding = get_embedding(ai_sentence)
esg_embedding = get_embedding(esg_term)

cosine_similarity = np.dot(ai_embedding, esg_embedding.T) / (
    np.linalg.norm(ai_embedding) * np.linalg.norm(esg_embedding)
)
```

For instance, BERT facilitates the identification of subtle semantic links between AI-related innovations and ESG-specific goals, such as carbon reduction or operational transparency.

AI, AI Products, AI Chips, Machine Translation, Machine Learning, Computer Vision, Human-Computer Interaction, Deep Learning, Neural Network, Biometrics Identification, Image Recognition, Data Mining, Feature Extraction, Voice Synthesis, Speech Recognition, Knowledge Graph, Intelligent Banking, Intelligent Insurance, Human-machine Cooperation, Intelligent Supervision, Intelligent Education, Intelligent Customer Service, Intelligent Retail, Intelligent Agriculture, Robo-adviser, Augmented Reality, Virtual Reality, Intelligent Medicine, Smart Speaker, Intelligent TTS, Smart Government Service, Autonomous Driving, Intelligent Transportation, Convolutional Neural Network, Voiceprint Recognition, Feature Extraction, Driving-less technology, Intelligent Home, Q&A System, Face Recognition, Business Intelligence, Smart Finance, Recurrent Neural Network, Reinforcement Learning, Agent, Intelligent Elderly Care, Big Data Marketing, Big Data Risk Control, Big Data Analysis, Big Data Processing, Support Vector Machine (SVM), Long Short-term Memory (LSTM), Robotic Process Automation, Natural Language Processing, Distributed Computing, Knowledge Representation, Smart Chips, Wearable Products, Big Data Management, Intelligent Sensor, Pattern Recognition, Edge Computing, Big Data Platform, Intelligent Computation, Intelligent Search, Internet of Things, Cloud Computing, Augmented Intelligence, Voice Interaction, Intelligent Environmental Protection, Human-computer Dialogue, Deep Neural Network, Big Data Operation

Fig. 2. AI dictionary for text tokenisation

Environmental, Social and Governance (ESG). In accordance with the findings of Lu et al. [48], this study employs data derived from the ESG rating system established by the China Securities Index Company. The ESG performance is categorised into nine grades, with a scoring system that assigns points ranging from 1 to 9 for evaluation purposes. The evaluation framework comprises three primary indices—environment, society, and governance—alongside 14 secondary indices and over 130 underlying data indices.

Given that the ESG evaluations are updated quarterly, this study uses the average of the four quarterly ratings to represent the annual data, ensuring consistency and reducing the potential for seasonal bias. The aggregated ESG score reflects an overall assessment of firms' sustainability practices.

Fig. 3 illustrates the hierarchical structure of the ESG evaluation framework, detailing the relationships between primary indices, secondary indices, and underlying metrics.

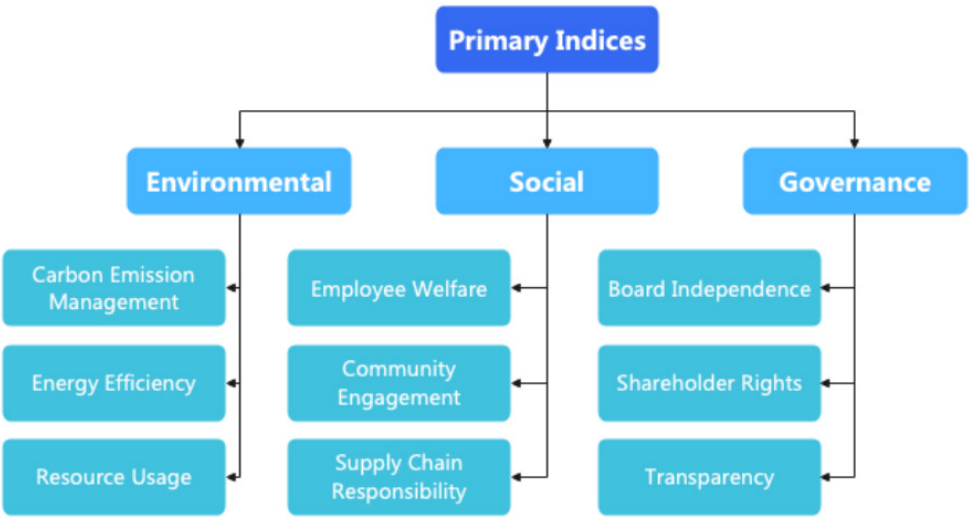

Fig. 3. Hierarchical structure of the ESG evaluation framework

Green Technology Innovation. Green technology innovation (g_patents) and ownership concentration (TOP1). In measuring green technology innovation, green invention patents and green utility model patents are typically considered. Invention patents refer to innovative technological achievements or conceptual solutions that can be directly applied in production. In contrast, utility model patents pertain to innovative designs proposed for the appearance or structure of a product, which generally build upon existing products. This study collects data on companies' green patent applications to evaluate the level of green technology innovation within enterprises. Then, this study uses the ratio of the largest shareholder's ownership stake to the company's total share capital to assess ownership concentration.

Control Variables. This study incorporates a series of control variables to mitigate potential biases and ensure robust estimations. Firm size (Size) is included, measured as the natural logarithm of total assets. Firm age (FirmAge) is calculated as the difference between the observation year and the establishment year. This variable captures the influence of organisational maturity. The asset-liability ratio (Lev) is used as a proxy for financial leverage, reflecting the firm's risk profile. The net profit rate on total assets (ROA) measures profitability and its potential impact on ESG initiatives.

Dual-role integration (Board) is used to capture the potential influence of corporate governance. Liquidity ratio (Liquid) is calculated as the ratio of current assets to current liabilities, and it reflects the firm's short-term solvency. Ownership nature (SOE) is included as a binary variable to distinguish state-owned enterprises from non-state-owned enterprises. Additionally, asset growth rate (Growth) is included to account for the firm's expansion dynamics.

Time and industry dummy variables are also incorporated to control for temporal and sectoral fixed effects. They are used to ensuring that unobserved heterogeneity does not confound the results.

3.3 Model Setting

The main effect regression model is constructed in Formula (1)-(3).

$$ESG_{i,t} = \beta_0 + \beta_1 AI_{i,t} + \varepsilon_{i,t} \tag{1}$$

$$ESG_{i,t} = \beta_0 + \beta_1 AI_{i,t} + Year_t + Industry_i + \varepsilon_{i,t} \tag{2}$$

$$ESG_{i,t} = \beta_0 + \beta_1 AI_{i,t} + \beta_n C_{i,t} + Year_t + Industry_i + \varepsilon_{i,t} \tag{3}$$

The mediating effect models are constructed in Formulas (4)-(5).

$$g\_patents_{i,t} = \beta_0 + \beta_1 AI_{i,t} + \beta_n C_{i,t} + Year_t + Industry_i + \varepsilon_{i,t} \tag{4}$$

$$ESG_{i,t} = \beta_0 + \beta_1 g\_patents_{i,t} + \beta_2 AI_{i,t} + \beta_n C_{i,t} + Year_t + Industry_i + \varepsilon_{i,t} \tag{5}$$

The moderating effect model is constructed in Formula (6).

$$ESG_{i,t} = \beta_0 + \beta_1 AI_{i,t} \times TOP1_{i,t} + \beta_2 AI_{i,t} + \beta_3 TOP_{i,t} + \beta_n C_{i,t} + Year_t + Industry_i + \varepsilon_{i,t} \tag{6}$$

The moderated mediation effect model is constructed in Formula (7)-(8).

$$g\_patents_{i,t} = \beta_0 + \beta_1 AI_{i,t} \times TOP1_{i,t} + \beta_2 AI_{i,t} + \beta_3 TOP_{i,t} + \beta_n C_{i,t} + Year_t + Industry_i + \varepsilon_{i,t} \tag{7}$$

$$\begin{aligned} ESG_{i,t} = {} & \beta_0 + \beta_1 AI_{i,t} \times g\_patents_{i,t} \\ & + \beta_2 AI_{i,t} + \beta_3 TOP_{i,t} + \beta_4 g\_patents_{i,t} \\ & + \beta_n C_{i,t} + Year_t + Industry_i + \varepsilon_{i,t} \end{aligned} \tag{8}$$

where:

i and t represent firm and year respectively.

β represents the parameters to be estimated.

C represents the control variables.

Year and *Industry* denote year and industry fixed effects respectively.

ESG is the ESG performance.

AI represents AI technology.

g_patents and *TOP*1 represent green technology innovation and ownership concentration respectively.

ε Denotes the error term.

3.4 Test Procedure

The test procedure involves examining the relationships between AI adoption, green technology innovation, and ESG performance using baseline regression models. Mediation analysis is conducted to test whether green technology innovation serves as an intermediary factor linking AI adoption to ESG performance. To ensure robustness, additional tests are performed. This includes alternative variable specifications and sensitivity analyses. Industry and year fixed effects are incorporated throughout to control for unobserved heterogeneity.

Table 1. The specific operation steps of the algorithm

Empirical Analysis
Step 1: Measurement of Variables
1: Measure AI technologies (AI) using word frequency statistics from annual reports, representing the independent variable.
2: Measure ESG performance (ESG) using the ESG ratings of Huazheng as the dependent variable.
3: Measure green technology innovation (g_patents) using the logarithm of patent applications, which serves as a mediating variable.
4: Measure ownership concentration (Top1) using the ratio of the largest shareholder's ownership stake to the company's total share capital, representing the moderating variable.
Step 2: Testing Hypothesis
1: Construct the baseline regression model to test the direct effect of AI technology on ESG. Estimate the model using OLS, accounting for industry and year fixed effects to validate H1.
2: Construct the mediating regression model to test the indirect effect of green technology innovation played in the relationship between AI technology and ESG. Estimate the model using OLS, accounting for industry and year fixed effects to validate H2.
3: Construct the moderated mediating regression model to test the indirect effect of ownership concentration played in the relationship between AI technology and ESG. Estimate the model using OLS, accounting for industry and year fixed effects to validate H3 and H4.
Step 3: Robustness Checks
1: treat AI with one period lag to test the impact of AI on ESG, ensuring the robustness of H1.
2: Shorten the sample period to 2013-2022 to test the impact of big data proliferation, ensuring the robustness of H1.

4 Empirical Results

4.1 Descriptive Statistics Results

Descriptive statistics are presented in Table 2. The mean degree of AI is 0.786, with a standard deviation (SD) of 1.165 and a median of 1.165. This suggests a relatively normal distribution, characterized by limited variation in stock price volatility across different firms. In terms of environmental, social, and governance (ESG) metrics, the SD is 1.017, with minimum and maximum values of 1.250 and 6.250, respectively. The data exhibits only slight variation, as indicated by the average value of 4.111, which exceeds the median of 4.000, suggesting that most firms have ESG scores that fall within a higher range. For the variable g_patents, the SD is 6.292, indicating significant variability within each data group. Similarly, for the variable TOP1, the SD is 14.765, also reflecting considerable variation across the data groups. The statistics for the control variables are consistent with findings reported in the existing literature.

Table 2. Summary statistics

Variables	Observations	Mean	SD	Min	Median	Max
AI	37120	0.786	1.165	0.000	0.000	4.500
g_patents	37120	1.876	6.292	0.000	0.000	46.000
ESG	37120	4.111	1.017	1.250	4.000	6.250
TOP1	37120	34.480	14.765	9.125	32.204	74.451
Size	37120	22.213	1.302	19.857	22.022	26.245
FirmAge	37120	2.902	0.339	1.792	2.944	3.526
Lev	37120	0.431	0.207	0.055	0.424	0.902
ROA	37120	0.040	0.065	-0.227	0.038	0.224
Board	37120	2.124	0.200	1.609	2.197	2.708
Liquid	37120	2.420	2.433	0.313	1.645	15.801
SOE	37120	0.368	0.482	0.000	0.000	1.000
Growth	37120	0.168	0.412	-0.577	0.105	2.581

4.2 Regression Results of the Main Effects

Linear Fitting Results of Main Effects. The scatter plot of linear regression is a graphical tool used to visualize the relationship between two variables. When interpreting and analyzing a linear regression model, the scatter plot can provide intuitive and significant insights. In Fig. 4, each point represents an observation in the dataset, with the horizontal axis representing the independent variable (AI) and the vertical axis representing the dependent variable (ESG). A fitted line is typically drawn in the scatter plot, calculated through the linear regression model, and aims to best represent the data points. The results indicate that the relationship between AI and ESG is characterized by data points that are roughly distributed along an upward-sloping straight line from the lower left to the upper right. As the AI variable increases, the ESG variable also tends to increase, indicating a positive linear relationship between the two.

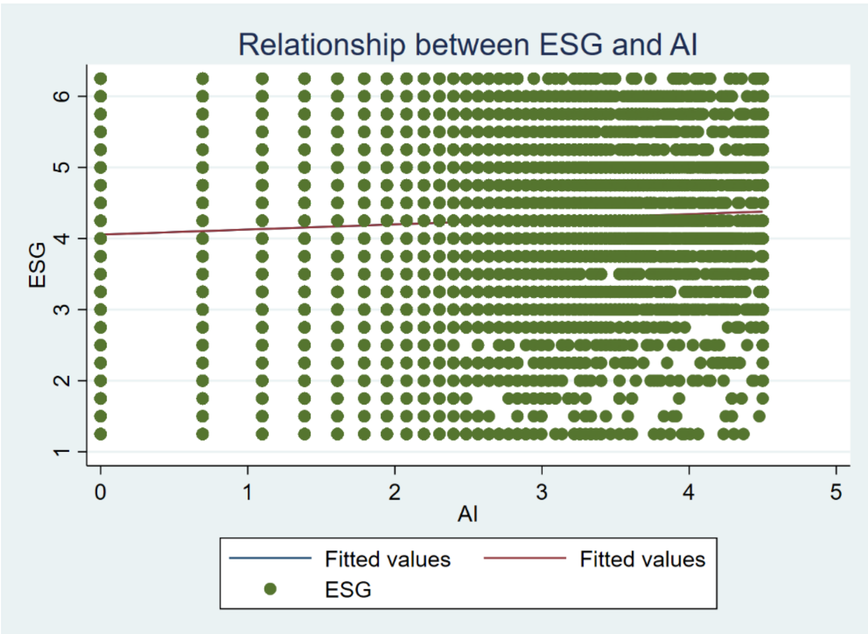

Fig. 4. Scatter plot of the linear regression between ESG and AI

Ordinary Least Squares Results of the Main Effects. In the benchmark regression analysis, we employed three tests (see Table 3). First, Column (1) presents the basic model without fixed effects or control variables, clearly illustrating the direct relationship be-tween the independent and dependent variables. The results indicate that artificial intelligence (AI) can significantly enhance environmental, social, and governance (ESG) performance, with significance at the 1% level. Second, Column (2) introduces a model with fixed effects, incorporating both year and industry fixed effects. By accounting for group or time specificity, this model more accurately captures factors that remain constant over time but influence the dependent variable, thereby improving the precision of the regression results. The findings again demonstrate that AI can significantly enhance ESG performance, with significance at the 1% level. Finally, the most complex model includes both fixed effects and control variables. This model not only accounts for differences between groups and over time but also further mitigates omitted variable bias by comprehensively capturing various influencing factors. As a result, it yields more accurate and reliable regression outcomes. The results indicate that AI can significantly enhance ESG performance, with significance at the 1% level.

Table 3. Benchmark regression results

	(1) ESG	(2) ESG	(3) ESG
AI	0.072***	0.076***	0.066***
	(15.965)	(13.357)	(12.489)
Size			0.259***
			(51.565)
FirmAge			-0.221***
			(-13.095)
Lev			-0.926***
			(-23.560)
ROA			2.695***
			(28.131)
Board			-0.131***
			(-4.980)
Liquid			-0.005**
			(-2.087)
SOE			0.155***
			(13.481)
Growth			-0.098***
			(-7.509)
_cons	4.054***	4.051***	-0.501***
	(639.115)	(591.049)	(-4.182)
N	37120	37120	37120
adj. R^2	0.007	0.051	0.188

t statistics in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

4.3 Regression Results of the Mediating Effects and Moderating Effects

Linear Fitting Results of Mediating Effects. Fig. 5 displays observations where the horizontal axis represents the independent variable AI and the vertical axis represents the dependent variable g_patents. A fitted line from the linear regression model illustrates that data points are generally aligned along an upward slope. This indicates a positive linear relationship, where increases in AI correspond to increases in g_patents. Fig. 6 shows each point as an observation in the dataset, with g_patents on the horizontal axis and ESG on the vertical axis. The scatter plot includes a fitted line from a linear regression model that represents the data distribution. The results indicate a positive linear relationship, with data points aligned along an upward slope; as g_patents increases, ESG also tends to increase.

Ordinary Least Squares Results of the Mediating Effects and Moderating Effects. As presented in Table 4, the results in column (1) of the model assessing the impact of artificial intelligence (AI) on green patents (g-patents) reveal a positive relationship, evidenced by a regression coefficient of 0.782, which is statistically significant at the 1% level. Additionally, in column (2), where the model examines the effect of AI on environmental, social, and governance (ESG) criteria while incorporating g-patents, the findings indicate that g-patents exert a positive influence on ESG, with a regression coefficient of 0.012, also significant at the 1% level. These results suggest that the mediating effect of g-patents is indeed significant.

As shown in Table 4, the third column presents the model assessing the impact of artificial intelligence (AI) on environmental, social, and governance (ESG) factors. This model incorporates AI, TOP1, and the interaction term between AI and TOP1. The results show that the interaction term between AI and TOP1 has a positive impact on ESG, with a regression coefficient of 0.001, which is statistically significant at 1% level. This finding suggests that the regulatory role of TOP1 is significant.

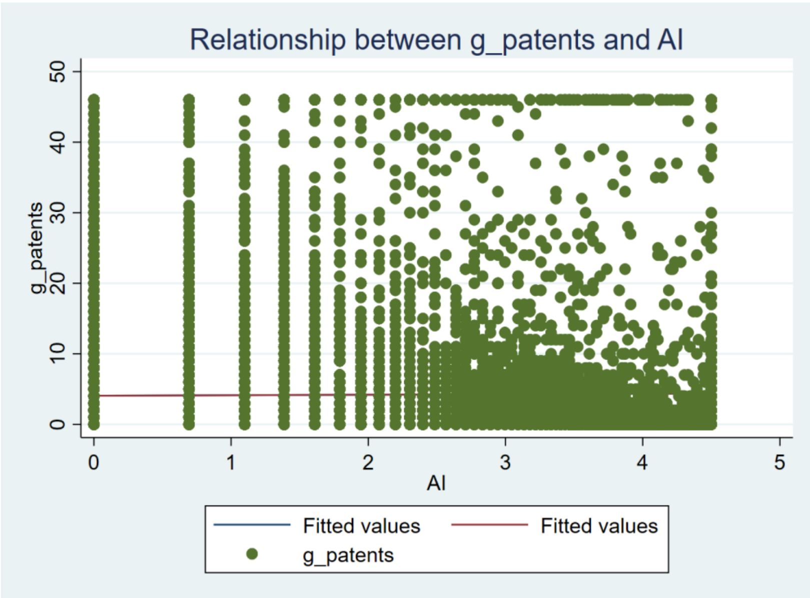

Fig. 5. Scatter plot of the linear regression between g_patents and AI

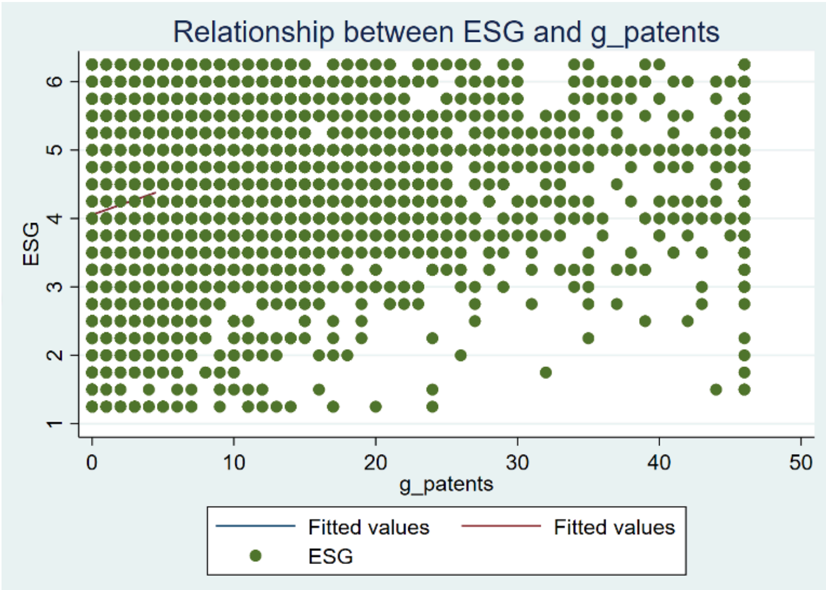

Fig. 6. Scatter plot of the linear regression between ESG and g_patents

Table 4. Results of mediation analysis and mediation analysis

	(1)	(2)	(3)
	g_patents	ESG	ESG
AI	0.782***	0.056***	0.031***
	(18.576)	(10.666)	(2.632)
Size	1.310***	0.243***	0.256***
	(26.462)	(47.098)	(50.585)
FirmAge	-0.824***	-0.211***	-0.210***
	(-7.306)	(-12.533)	(-12.354)
Lev	0.760***	-0.935***	-0.927***
	(3.325)	(-23.890)	(-23.637)
ROA	3.025***	2.658***	2.616***
	(6.441)	(27.826)	(27.208)
Board	0.238	-0.133***	-0.117***
	(1.250)	(-5.097)	(-4.467)
Liquid	0.021*	-0.006**	-0.006**
	(1.859)	(-2.191)	(-2.218)
SOE	0.224***	0.152***	0.145***
	(2.930)	(13.274)	(12.402)
Growth	-0.365***	-0.094***	-0.096***
	(-5.974)	(-7.201)	(-7.290)
g_patents		0.012***	
		(15.524)	
inter1			0.001***
			(3.593)
TOP1			0.001***
			(2.669)
_cons	-26.462***	-0.180	-0.530***
	(-23.651)	(-1.472)	(-4.406)
N	37120	37120	37120
adj. R^2	0.114	0.193	0.189

t statistics in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

In addition, it is performed a moderated mediation effect analysis. As shown in Table 5, column (1) in-corporates AI, TOP1, and the interaction between AI and TOP1 into the model evaluating the impact of AI on g patents. The results showed that the interaction terms of AI and TOP1 had a positive effect on gatats, and the regression coefficient was 0.006, which was statistically significant at the 5% level. In column (2), we include AI, TOP1, g-paters, and interaction term models among AI to assess the impact of AI on ESG. The results show that the interaction term between AI and TOP1 positively affects ESG with a regression coefficient of 0.001, which is significant at the 1% level. Thus, the mediating role of TOP1 was confirmed.

Table 5. Results on moderated mediation analysis

	(1)	(2)
	g_patents	ESG
AI	0.579***	0.024**
	(6.338)	(2.045)
TOP1	-0.003	0.001***
	(-1.101)	(2.759)
inter1	0.006**	0.001***
	(2.449)	(3.384)
Size	1.311***	0.240***
	(26.571)	(46.216)
FirmAge	-0.824***	-0.200***
	(-7.268)	(-11.800)
Lev	0.739***	-0.936***

	(3.245)	(-23.957)
ROA	2.867***	2.581***
	(5.968)	(26.924)
Board	0.259	-0.121***
	(1.359)	(-4.592)
Liquid	0.021*	-0.006**
	(1.782)	(-2.318)
SOE	0.216***	0.142***
	(2.801)	(12.209)
Growth	-0.360***	-0.091***
	(-5.913)	(-6.987)
g_patents		0.012***
		(15.446)
_cons	-26.423***	-0.211*
	(-23.531)	(-1.721)
N	37120	37120
adj. R^2	0.115	0.194

t statistics in parentheses; * p < 0.1, ** p < 0.05, *** p < 0.01

4.4 Robustness Test

In a comprehensive examination of AI's impact on ESG criteria, implementing a cycle of delayed therapy is a methodologically sound strategy aimed at mitigating potential endogenetic concerns. This approach ensures that advances in AI precede and may have an impact on ESG performance, rather than the other way around. The findings in column (1) of Table 6 show that AI has a beneficial effect on ESG, thus providing preliminary evidence for a positive correlation between technological progress and sustainability. In addition, by narrowing the study time frame to 2013 to 2022, we continue to observe a positive impact of AI on ESG. This observation in column (2) further strengthens the robustness of the results, as it shows that this positive relationship remains consistent across time contexts. This consistency helps reduce potential distortions caused by anomalies in the overall conclusions drawn from the studies.

Table 6. Robustness test results

	(1) ESG	(2) ESG
L.AI	0.067***	
	(11.474)	
AI		0.067***
		(12.172)
Size	0.261***	0.261***
	(48.946)	(45.798)
FirmAge	-0.230***	-0.225***
	(-12.272)	(-11.175)
Lev	-0.868***	-0.980***
	(-20.428)	(-21.681)
ROA	2.856***	2.885***
	(27.697)	(27.178)
Board	-0.134***	-0.133***
	(-4.758)	(-4.433)
Liquid	0.000	-0.006*
	(0.049)	(-1.798)
SOE	0.187***	0.180***
	(15.274)	(13.401)
Growth	-0.090***	-0.106***
	(-6.364)	(-7.087)

_cons	-0.570***	-0.548***
	(-4.444)	(-3.958)
N	32055	30391
adj. R^2	0.199	0.190

t statistics in parentheses; * p < 0.1, ** p < 0.05, *** p < 0.01

5 Discussion

5.1 Theoretical Contribution

This study will integrate computer technology into environmental, social and governance (ESG) management, and promote ESG management theory. Through the effective application of data processing and analysis, it provides precise theoretical support for research and promotes innovation in the field. This study explores how artificial intelligence (AI) can improve enterprise ESG performance, introducing a technology-driven perspective to ESG management. By establishing a theoretical framework, the research shows that AI can efficiently process data, identify ESG risks and opportunities, optimise decision making, and improve the overall nature of ESG functions. The framework enriches ESG's management theory and provides a new perspective on the integration of AI and sustainability. This study introduces the mediating role of green technology innovation in improving ESG performance of enterprises through artificial intelligence technology, and creates a new theoretical framework for enterprises' green transformation. Research shows that artificial intelligence technology is beneficial to the development and application of green technology innovation, and improves the ESG performance of enterprises. This discovery deepens our understanding of the relationship between green technology innovation and corporate sustainability and provides new theoretical and technical support for the theory of technological innovation in ESG management. This study explores the positive moderating effect of ownership concentration on ESG performance and green technology innovation. It provides new insights into the relationship be-tween corporate governance, technological innovation, and sustainable development, enriches corporate governance theory, and illuminates how equitable structures affect innovation strategies and sustainability.

5.2 Practical Contribution

According to the needs of enterprises, this research has pioneered the application of computer technology in enterprise ESG management. An intelligent, customised ESG management system has been developed to provide businesses with a tool to improve efficiency and effectiveness while promoting the wider application of technology in sustainability. This study provides practical guidance for enterprises to optimise ESG management by using artificial intelligence. It facilitates the creation of an intelligent ESG management system for automated data collection, analysis, and visualisation, enabling companies to effectively identify ESG-related risks and develop targeted improvement strategies to enhance ESG functionality and sustainability.

To make these insights actionable, firms should prioritise the adoption of AI-driven tools tailored to their specific ESG needs. For instance, predictive analytics powered by AI can help companies forecast environmental risks, such as carbon emission trends, and proactively develop mitigation strategies. Companies can also implement AI-powered platforms to automate ESG reporting processes, reducing human error and improving transparency. Furthermore, integrating AI into supply chain management can enhance resource efficiency, minimise waste, and track compliance with sustainability standards, thereby contributing to overall ESG performance.

For policymakers, promoting the development of AI technologies in ESG management can have transformative effects. Supporting AI-driven sustainability innovations through funding, offering tax incentives for firms investing in green technology, and establishing clear regulatory frameworks for ESG data standardisation can encourage broader adoption of these practices. Policymakers can also facilitate public-private partnerships to advance research and the implementation of AI in corporate ESG strategies.

Moreover, this study demonstrates how green technology innovation moderates the impact of artificial intelligence technology on the ESG performance of enterprises and provides a practical approach for green transformation. Encouraging investment in green technology research and development, promoting commercialisation, improving economic and environmental benefits, and enhancing market competitiveness are critical steps for enterprises. Furthermore, the research on the role of centralised ownership supervision provides guidance for optimising ownership structures and governance. By adjusting the concentration of ownership, companies can enhance technological innovation, improve ESG performance, promote green innovation, and achieve long-term stability and social responsibility.

5.3 Limitations and Future Research

Research on the impact of AI on ESG of listed companies in China faces several data limitations, such as the lack of richness, standardisation, transparency of unstructured data, and constraints related to historical data. These challenges affect the accuracy and robustness of AI models. Future research should aim to address these issues by enhancing the collection and processing of data, applying advanced NLP methods to better analyse unstructured data, promoting standardisation and visibility of ESG datasets. Leveraging interdisciplinary collaboration can also enrich ESG data dimensions, while establishing a long-term data tracking mechanism will facilitate regular updates and continuous improvement in data quality.

The reliance on keyword frequency statistics to assess a company's AI capabilities has evident limitations. These statistics may fail to fully capture the scope of AI adoption due to inconsistencies in keyword selection and weighting, as well as variations in corporate naming conventions, which can introduce errors. Additionally, keyword frequency does not adequately reflect the complexity or effectiveness of AI implementation. Future research should prioritise the integration of NLP techniques to improve semantic understanding and contextual analysis. By adopting multi-dimensional evaluation systems and engaging with industry experts, researchers can develop more rigorous and scientific evaluation criteria. These advancements will enable more accurate assessments of a company's AI capabilities and their impact on ESG outcomes, supporting both research and decision-making processes.

6 Conclusions

6.1 Theoretical Contributions

This paper provides an empirical analysis of the impact of artificial intelligence (AI) on the environ-mental, social, and governance (ESG) performance of companies in China's A-share market, exploring the mediating and moderating roles of green innovation and ownership concentration. The results demonstrate that AI significantly enhances firms' ESG performance, particularly in environmental and social responsibility. Regression analysis indicates that AI technology improves ESG scores by increasing operational efficiency and driving green innovation. Additionally, the study reveals a mediating effect of green patents, showing that AI fosters green technological innovation, which in turn boosts ESG performance. The moderating effect of ownership concentration is also confirmed, with the interaction between AI and ownership concentration significantly influencing ESG outcomes. Robustness tests further verify the positive impact of AI across different timeframes, underscoring its critical role in corporate sustainability. Overall, this research offers new insights into AI's contributions to corporate sustainability and provides valuable strategic recommendations for leveraging AI technology to enhance ESG performance during digital transformation. Future studies could explore industry and regional differences and further investi-gate the mechanisms through which AI affects social responsibility and corporate governance.

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