ingegneria sismica
International Journal of Earthquake Engineering
Anno XLIII - Num. 1 - 2026

The Bidirectional Relationship Between Corporate ESG Performance and Generative AI Governance: An Institutional Theory Perspective

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SUMMARY: *Under the conditions of constantly rising uncertainties in the development of the global economy and society, it becomes increasingly important to study the relationship between corporate ESG performance and generative AI governance. For this reason, the purpose of this study is to investigate the mutually causal relationship between corporate ESG performance (ESG) and generative AI governance (GAI) on the basis of institutional theory. Based on previous literature and theoretical analysis, four research hypotheses were formulated, and, at the same time, the sample size was selected, along with the source of information about the companies being analyzed. In this model of regression analysis, the effects of the dependent variables, independent variables, mediators, control variables, and moderators on one another are reflected. The regression model of analysis is used to verify the stated research hypotheses. When all other factors remain unchanged, there exists a significant mutual correlation of corporation ESG performance (ESG) and generative AI governance (GAI), which verifies hypotheses H1 and H2. Despite the presence of the enterprise life cycle (ELC) and industry classification (IC) in the analysis, a significant mutual correlation of corporation ESG performance (ESG) and generative AI governance (GAI) still exists.*

KEYWORDS: *ESG; generative AI; regression model; institutional theory*

1 Introduction

Due to the pursuit of the carbon goals and high-quality development, the corporate ESG performance has become an important indicator of measuring their sustainable capability [1]. In the last several years, with the rapid development of the digital economy, especially with the continuous evolution of the artificial intelligence technology, the progress in corporate green transformation and high-quality development has gained new impetus [2, 3]. The combination of greening and intelligentization has become an important approach through which enterprises can attain sustainable development. As a result, AI, which has a revolutionary impact in processing information and predicting and optimizing various tasks, is deemed to be an effective engine for promoting corporate ESG performance [4]. However, when using AI technology in ESG, the high technical complexity and unpredictable economic value are major problems that cannot be ignored. Hence, many companies need to depend on observing, learning and mimicking the behavior of other enterprises when making decisions and actions, which will generate a substantial AI herd effect [5, 6]. On the one hand, this phenomenon can promote enterprises' use of AI technology to improve their ESG performance; on the other hand,

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https://doi.org/10.65102/is2026140
Published: 30 April, 2026

without adequate capabilities and knowledge, enterprises may experience governance lag and ethical risks, which may hinder ESG performance [7, 8].

The effects of AI-led ESG practices are clearer when it comes to corporate sustainability as they represent the long-term consequences of financial performance and the empowerment brought about by intelligent technology [9]. Literature [10] administered a questionnaire among 200 managers and supervisors from state-owned enterprises (SOEs) on corporate sustainability. It was found out that AI technology will help increase sustainability through SOE behavior. In this case, ESG plays a mediating role between the use of AI technology and increased sustainability. Studies that have explored the effect of AI on ESG performance include reports on the innovative means of improving ESG reporting and development of ESG management platforms [11]. Literature [12] analyzed the influence of AI-based indices on global ESG index changes using a wavelet quantile-to-quantile regression model. According to literature, AI shows greater suppression effects on ESG performance in the short run; however, it helps improve ESG performance in the medium and long term. The literature review [13] on the effect of AI on the environmental, social, and governance (ESG) performance of businesses shows that the effect of AI on the target company's environmental and social performance is positive and significant. While the effect of AI on governance is also significant, it is much lower compared to other factors. The literature review [14] through the use of case studies proves that there is a direct positive effect between the adoption of AI by firms and ESG performance with digital maturity having a positive moderating effect. The literature review [15] used a model that showed that there is an interaction between AI and the performance of ESG in businesses with green innovation as a moderating mechanism. It was shown that AI use improves the performance of environmental, social, and governance, with green innovation mediating the effect positively. Similar results were obtained in literature [16].

The following literature systematically explores the impact mechanisms of artificial intelligence and group effects on corporate ESG performance. Literature [17] collected sector-unbalanced data from Chinese listed companies between 2007 and 2022. Through robustness tests, it demonstrated that AI development positively influences listed companies' ESG performance, primarily through enhancing total factor productivity and R&D expenditure. To identify the reasons behind AI's enhancement of corporate ESG performance, [18] developed a decision-making tool to identify environmental, social, and governance factors faced by small and medium-sized enterprises. They concluded that AI effectively optimizes organizational processes, reduces corporate costs, and improves governance in employee management models. Literature [19] indicates that more advanced AI technologies yield more significant improvements in corporate ESG performance. This is primarily because high-level AI technologies demonstrate greater advantages in optimizing resource allocation and enhancing production and supply chain efficiency, thereby improving corporate ESG outcomes. Literature [20] employed a least squares regression model to explore the mechanism through which AI technology influences corporate ESG performance. They found that AI application innovates corporate production processes, technologies, and management models, reduces corporate carbon emissions, and consequently enhances corporate ESG performance.

Previous research forms a basis for investigating how the use of AI by firms affects their corporate ESG performance and identifies how peer effects play a role in the operations of firms. Nevertheless, most scholars have mainly emphasized the effect of the application of AI by each firm in improving their ESG performance without considering how the collective impact and mechanisms created through peer effects can be realized due to the adoption of AI technology at the industrial level [21, 22]. Studying the mechanism through which AI adoption contributes to ESG performance shows how the firms learn and improve their sustainable development initiatives by adopting from their peers when making transformations towards becoming smart and green [23, 24].

This paper introduces the research hypotheses about the mutual relationship between the ESG performance of companies and GAI governance, based on key theoretical perspectives. These hypotheses are labeled as H1 to H4. Based on relevant materials and literature, the company samples used in this research, as well as data sources, will be determined, together with the research variables such as the dependent variable, independent variables, mediating variables, control variables, and moderating variables. In the following step, a regression model will be formulated. Prior to examining the mutual relationship between the ESG performance of companies and GAI governance, data distributions and interrelations among the research variables will be examined.

2 Core Concepts and Research Hypotheses

2.1 Core Concepts

2.1.1 Corporate ESG Performance

ESG Performance measures corporate performance in terms of the firm's actions in environmental, social, and governance terms [25]. In other words, the environmental indicators include measures of how a firm manages its environment impact, which may involve lowering emissions, saving energy, and using sustainable resources. On the other hand, the social indicators measure the obligations of firms in relation to their workers, customers, and the wider society, which may involve issues relating to labor relations, safety of products, and societal issues. Governance indicators measure the organizational structure and practices used by the organization in conducting business activities in a transparent manner. This measure is an indication of the success of a firm in implementing its ESG strategy [26]. The measure of ESG Performance employs many indicators. To begin with, environmental performance measures include carbon footprint which is usually calculated based on carbon dioxide equivalents representing total amount of green-house gases emitted by an organization. Energy efficiency includes measures such as total energy use and percentage of renewable energy being used. Measures related to water resources include water efficiency and management while waste management usually involves assessing the recycling rate and waste management techniques used. As for social performance metrics, they include measures related to workforce demographics such as the percentage of female employees and ethnic minority groups and pay gaps between male and female employees. In terms of satisfaction and well-being, employee turnover, benefit packages provided and safety records can be assessed. In consumer satisfaction measures, product and services satisfaction are measured using surveys and complaints. Contributions to communities include corporate investment in welfare and community support projects. Finally, with regards to corporate governance performance, measures include board composition with particular focus on independence and diversity of directors. Measures of transparency include financial transparency and ESG-related reporting. Corporate compliance can be measured in terms of absence of corruption and conflicts of interest, as well as litigation history.

2.1.2 Generative AI Governance

The fundamental principle underlying generative AI governance is the engagement of many parties in the governance process, relying on the dynamism of each governance organization to make continuous improvements to governance methods. In doing so, social welfare will be optimized, and possible hazards will be controlled effectively. Institutional theory posits that all parties should create an institutional space that accommodates collaborative participation. Generative AI governance requires multi-stakeholder participation, which entails a multidimensional process. From the regulatory perspective, various stakeholders such as government organizations, industry associations, enterprises, research institutions, and the public occupy different nodes, constructing a network of rules and regulations pertaining to AI safety and ethics. Firstly, governments play a major role in regulating the AI field by establishing legislation and policy guidelines to safeguard AI governance from a legal perspective. For example, the construction of safety assessment and review mechanisms for generative AI creates essential criteria for industrial development, with strict governance and security policies enforced in important sectors. Secondly, enterprises need to perform micro-regulation tasks in the AI industry. As innovators and suppliers of AI products, enterprises must comply with the legal requirements of AI development in their external environment. Enterprises are expected to develop effective governance management mechanisms, abide by industry ethics, and promote the development of AI.

2.1.3 Corporate Life Cycle

The business life cycle is subdivided into five distinct phases: start-up, growth, maturity, turbulence, and decline. In this study, companies are segmented based on their location in the life cycle of businesses. Considering that the sample in the study comprises publicly held firms, which have largely exceeded the start-up stage, the start-up and growth phases are merged to become one growth stage for purposes of classification. Additionally, the turbulence phase samples with attributes similar to those of mature companies are placed in the mature category. Similarly, the turbulence phase samples with attributes similar to those of companies in the decline phase are classified under the decline category.

2.1.4 Industry Classification

This paper first categorizes enterprises into manufacturing and service industries. Since capital goods enterprises are excluded from our analysis, the resulting industry classifications are termed intermediary industries and final consumption industries. For the service sector, we reference relevant documents such as the National Bureau of Statistics' Statistical Classification of Production-Oriented Services and Statistical Classification of Life-Oriented Services to divide services into production-oriented services and life-oriented services. Building upon this industry classification framework, to better elucidate subsequent research findings, we further categorize enterprise types. Intermediary-type enterprises in manufacturing and production-oriented service enterprises in the service sector are grouped as “intermediary enterprises.” Meanwhile, final consumption-type enterprises in manufacturing and lifestyle-service enterprises in the service sector are collectively termed “mass-market enterprises.”

2.2 Research Hypotheses

Corporate ESG performance improves generative AI governance. As such, we formulate hypothesis H1: Corporate ESG performance is positively related to generative AI governance.

Generative AI governance boosts corporate ESG performance, suggesting a bidirectional relationship between the variables. As such, we formulate hypothesis H2: Generative AI governance is positively related to corporate ESG performance.

Corporate ESG performance may help boost environmental management, social responsibility, and governance accountability. According to institutional theory, organizations that have adopted ESG performance are likely to exhibit improved generative AI governance, thereby extending their lifecycles. On the other hand, organizations that enjoy prolonged lifecycles may exhibit improved ESG performance and generative AI governance. As such, we formulate hypothesis H3: Corporate lifecycle partially mediates the bidirectional relationship between ESG performance and generative AI governance.

Prior studies show that industry categorization moderates the bidirectional relationship between corporate ESG performance and generative AI governance. As such, we formulate hypothesis H4: Industry categorization moderates the relationship between corporate ESG performance and generative AI governance.

3 Study Design

3.1 Sample Selection and Data Sources

3.1.1 Sample Selection

In the empirical study conducted in this paper, to make sure that the research can be performed accurately, the research sample composed of listed companies within the period 2014-2023 was carefully filtered and processed. This process of data filtering helps to reduce several influences which could otherwise distort the results of the research. Finally, in order to prevent the impact that outliers might have on the results, this study used tail trimming in 1% and 99% percentiles of all variables in order to eliminate the effects brought by outliers on regression results. In the end, Figure 1 shows the distribution of the sample where numbers indicate the proportion(number) of the corporate samples. After the above-mentioned rigorous data processing procedures, this study was able to acquire 21,660 valid company samples. Such samples are highly representative and reliable, providing a solid base for the following research.

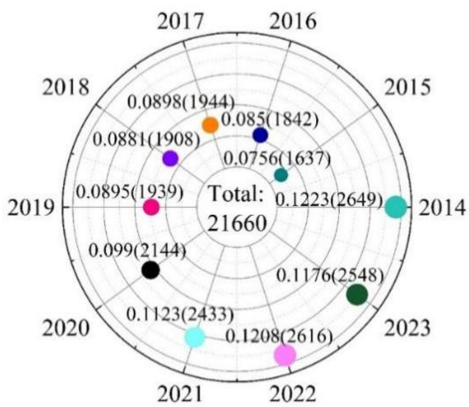


Figure 1: Distribution of sample situation

3.1.2 Data Sources

This research relies on data that have been sourced from two major sources: the NRDS and the SMAR databases. This work also omitted all observations that contained any data anomalies for important variables used in this study to make sure future research results would be reliable.

3.2 Research Variables

3.2.1 Dependent Variable

A special index provided by the CNRDS was employed to assess the GAI governance in the companies [27]. It measures the level of GAI integration into the enterprises based on certain criteria, such as investment in GAI, readiness of infrastructure, specialized talent pool, as well as concrete examples of GAI integration, especially with regard to product development, process optimization, and decision support systems. The index varies between 0 and 5.

3.2.2 Explanatory Variables

The ESG rating system is critically important in capital markets because of its high level of scientific accuracy and applicability. It is based on the fundamentals of ESG theory and contemporary international practice and uses market specifics to form an elaborate and highly detailed indicator structure. In total, the system consists of three primary indicators that can be further subdivided into ten secondary and thirty tertiary ones. With in-depth analysis of 125 metrics, it allows for precise assessments of the ESG performance of all listed enterprises and many bond issuers. This methodology contributes not only to improving the accuracy of evaluations but also to making informed decisions when investing in green projects. The ESG rating system defines fifty essential indicators covering environmental, social, and governance aspects taking into account corporate needs and market requirements. Due to such features, this study relies on ESG rating grades to assess ESG disclosure levels. To be specific, ratings between C and AAA will receive scores from 0 to 10, referred to as the ESG Score. This type of scoring system is not only able to reflect a company's ESG performance rating logically but also facilitates a horizontal comparison of ESG performance ratings among companies. It should be noted that this ESG evaluation system remains improving. Due to the continuing development of capital markets and the continuous promotion of ESG philosophy, this ESG evaluation system will become even more important for promoting sustainability in corporate management and the transparency of capital markets.

3.2.3 Mediating Variables

Having made an overall consideration about the evaluations provided by stakeholders concerning the stages of the corporate life cycle, 20 indicators have been chosen to build up a life cycle assessment model. Using factor analysis method, we calculate the score of the corporate life cycle. Companies will then be classified into ten groups according to their life cycle score, which ranges from 0 to 5. This methodology and its outcomes will be adopted in this paper to measure corporate life cycles.

3.2.4 Control Variables

After detailed review of the related literature, the following control variables were chosen for constructing the model: Firstly, in light of the company’s capital structure and ability to pay its debts, the debt to asset ratio (Lev) was chosen. Secondly, to consider the equity structure of the company, especially the effect of large shareholders, Top1 was chosen as the control variable. Moreover, to determine the profitability of the firm, the return on assets (ROA) was taken as a control variable. Also, the book-to-market ratio (BM) is used as a measurement tool for calculating the difference between a company’s book value and market value. At the same time, considering the effects of audit quality on accounting practices, Big Four accounting firms are considered control variables. Moreover, the age of the firm (FA) and size of the firm (Size) play a crucial role in determining ESG performance and governance in generative AI, and hence both have been chosen as control variables.

3.2.5 Control Variables

Industry Classification (ER) can be seen as a general term referring to the government’s policy measures intended to stimulate enterprise development. It takes on a moderating role within the interaction between corporate ESG and generative AI governance. In order to empirically quantify industry classification, this paper uses text analysis techniques to compute the number of appearances of industry-related words in the annual report of administrative district governments.

3.3 Model Construction

The econometric models used to examine the hypotheses in this paper are as follows:

Model 1 (H1): Corporate ESG performance has a positive correlation with generative AI governance (GAI). In other words:

$$GAI\_it = \beta_0 + \beta_1 ESG\_it + \beta_2 Controls\_it + Year\_t + industry\_i + \varepsilon\_it \tag{1}$$

Model 2 (H2): Generative AI governance (GAI) has a positive correlation with corporate ESG performance. In other words:

$$ESG\_it = \beta_0 + \beta_1 GAI\_it + \beta_2 Controls\_it + Year\_t + industry\_i + \mu\_it \tag{2}$$

Model 3 (H3): The Enterprise Life Cycle (ELC) acts as a mediator in the interactive relationship between corporate ESG performance and generative AI governance. In other words:

$$GAI\_it = \theta_0 + \theta_1 ESG\_it + \theta_2 ELC\_it + \theta_3 Controls\_it + Year\_t + industry\_i + \omega\_it \tag{3}$$

Model 4 (H4): Industry Classification (IC) moderates the interactive relationship between corporate ESG performance and generative AI governance. In other words:

$$\begin{aligned} GAI\_it = {} & \lambda_0 + \lambda_1 ESG\_it + \lambda_2 IC\_it + \lambda_3 (ESG\_it \times IC\_it) + \lambda_4 Controls\_it + \\ & Year\_t + industry\_i + \tau\_it \end{aligned} \tag{4}$$

i represents the firm, t denotes the year, GAI signifies generative AI governance, ESG indicates the firm's ESG performance, ELC denotes the firm's life cycle, IC represents industry classification, Controls denotes the vector of control variables, Year denotes the year fixed effect, Industry denotes the industry fixed effect, ε and μ, ω, τ denote error terms.

4 Empirical Research Analysis

4.1 Descriptive Statistics and Correlation Analysis

4.1.1 Results of Descriptive Statistical Analysis

The descriptive statistics for the research variables during the sample period on the aspects of corporate ESG performance, generative AI governance, enterprise lifecycle, industry classification, and control variables are provided in this section. The outcomes of the descriptive statistics are illustrated in Figure 2 below, where the color coding of the graph depicts the spread of data for the research variables among the 21,660 sample enterprises. Based on this distribution, the maximum value, minimum value, mean, and standard deviation can be determined. Figure 2 indicates that the mean for Generative AI Governance (GAI) is 3.884 with a standard deviation of 0.438. This suggests that the overall level of GAI among the sample enterprises is moderately low, though significant disparities exist in production efficiency across different firms. The mean value of ESG performance is 5.273, implying that the ESG rating of the sampled firms ranges from BBB to C. The lowest value of the enterprise life cycle (ELC) is 2.449, while the highest value is 5.296, implying that the sampled firms have reached the growth stage of the enterprise lifecycle. The highest value of the industry classification (IC) is 5.889, while the lowest is 2.367, implying that the government classification of industries for different sampled firms is relatively lower.

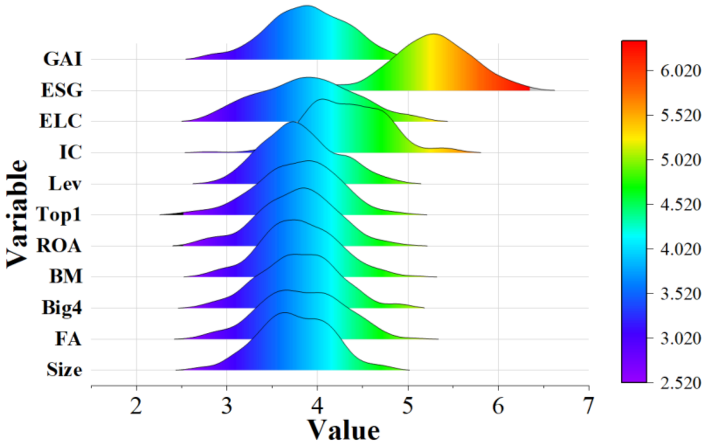
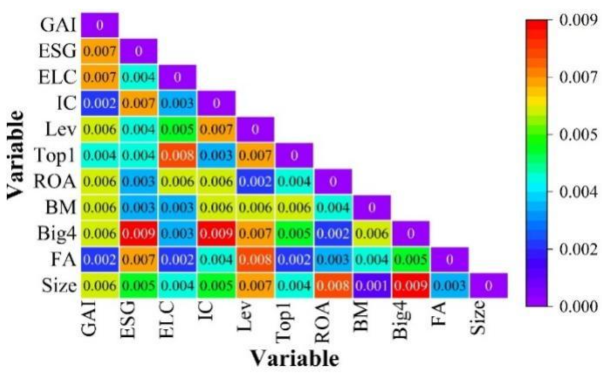


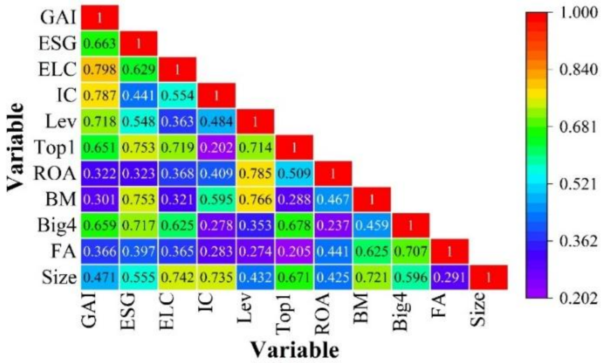
Figure 2: Descriptive statistical analysis results

4.1.2 Correlation Analysis

From the descriptive statistical analysis conducted above, the numerical ranges for each of the variables under investigation can be obtained. From this platform, Pearson correlation coefficients were used in examining correlations between the various research variables. Correlation analysis findings have been represented using the graph below showing (a) Pearson correlation coefficients and (b) Sig values. The variance inflation factors for the research variables are shown in Figure 4. The results indicate significant correlations between Generative AI Governance (GAI) and the following variables: - Corporate ESG Performance (ESG) - Corporate Life Cycle (ELC) - Industry Classification (IC) - Selected Debt-to-Equity Ratio (Lev) - Top Shareholder Ownership Ratio (Top1) - Return on Assets (ROA) - Book-to-Market Ratio (BM) - Big Four Accounting Firms (Big4) - Company Establishment Year (FA) - Company Size (Size) Company Establishment Age (FA), and Firm Size (Size). Their respective Pearson correlation coefficients are 0.663, 0.798, 0.787, 0.718, 0.651, 0.322, 0.301, 0.659, 0.366, 0.471, respectively. Their corresponding Sig values are 0.007, 0.007, 0.002, 0.006, 0.004, 0.006, 0.006, 0.006, 0.002, 0.006. The VIF values for all the study variables are less than three, namely 1.102, 1.914, 1.781, 1.066, 1.911, 1.245, 1.462, 1.237, 1.034, 1.537, and 1.838, respectively, as illustrated in figure 4 below.



(a)Pearson correlation coefficient



(b)Sig value

Figure 3: Results of correlation analysis

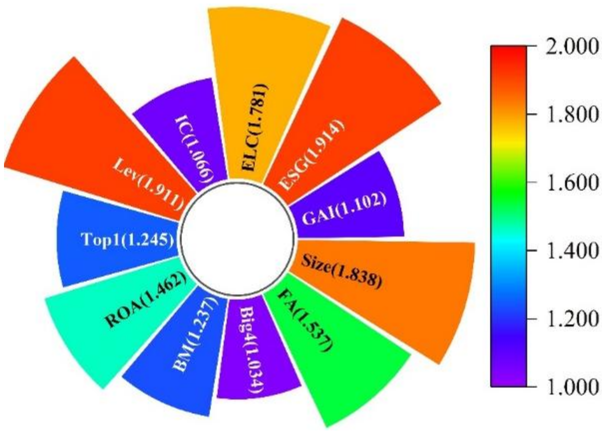


Figure 4: Study the variance inflation factor of the variable

4.2 Benchmark Regression Analysis

The above-stated framework has been used to measure the effect of corporate environmental, social, and governance (ESG) performance on generative AI governance (GAI), after accounting for time effects and industry effects by performing regression analysis with robust standard error. The benchmark regression results are shown in Table 1. In column (1), it can be observed that there is a relationship between corporate ESG performance (ESG) and generative AI governance (GAI), without considering any other variables in the regression model. It is evident from the regression coefficient of ESG performance (ESG), which is 0.306 and positively significant at 1%, which supports Hypothesis 1 and Hypothesis 2. In column (2), we have added other control variables to the above-stated regression model. It can be seen that the regression coefficient of ESG performance (ESG) is 0.031 and still positively significant at 1%. This shows that even when firm-specific factors are controlled for, the positive link between ESG performance and GAI still holds. Of the control variables, the coefficient for firm size (Size) is positively significant, meaning that bigger firms are more likely to realize efficiency improvements due to economies of scale. The coefficient for Firm Age (FA) is positively significant, implying that as firms age, their internal management structures improve, allowing them to develop internal controls that can enhance GAI. The coefficients for ROA and BM are positively significant, implying that profitable firms with strong growth potential are able to invest more in technology upgrades, hence raising their GAI levels. The coefficients for Big4 accountancy firms and the shareholding ratio of the most influential shareholder are 2.826 and 0.025, respectively. This implies that corporate governance is an important factor in raising GAI levels. By increasing oversight of management through larger boards and accounting teams, financial crisis behaviors are effectively reduced, fostering corporate innovation and promoting GAI advancement. The regression coefficients for the selected debt-to-asset ratio (Lev) are all significantly negative. Since a higher selected debt-to-asset ratio indicates a smaller value, this metric is more beneficial for a company's generative AI governance.

Table 1: Benchmark regression analysis results

Variable	(1)GAI	(2)GAI
ESG	0.306** (33.46)	0.026** (6.425)
Lev		-2.664*** (-5.227)
Top1		0.006*** (9.112)
ROA		2.826*** (27.645)
BM		4.723*** (21.367)
Big4		2.923*** (11.442)
FA		0.006*** (3.423)
Size		0.617*** (122.99)
Constant	13.451*** (219.33)	1.121*** (11.625)
Observations	12969	12969
Adjusted R-squared	0.216	0.736

4.3 Validation Analysis

4.3.1 Robustness Verification Analysis

In addition, this paper further evaluates the robustness of the benchmark regression by substituting the measurement metrics for both the explanatory variable and the response variable, changing the sample period, and including provincial fixed effects.

(1) Substituting ESG Performance Metrics

Because ESG performance depends on external agency assessments, any quantified measure of ESG performance by agencies might require substantial amounts of incomplete and ambiguous ESG data, thus causing considerable uncertainty regarding institutional ESG ratings. In view of such effects, this research substitutes ESG scores for Huazheng ESG institutional ratings as an alternative measure of ESG performance. As illustrated in Column (1) of Table 2 below, even after substituting the explanatory variable, corporate ESG performance (ESG) remains positively correlated with Generative AI Governance (GAI).

(2) Replacing Generative AI Governance (GAI) Metrics

When calculating generative AI governance (GAI) through the above model, some parameters are affected by some unpredictable variables, such as infrastructure preparedness and skilled manpower. Thus, manual calculation was applied to substitute for the generative AI governance indicator. The regression output is reflected in Column (2) of Table 2 and demonstrates that corporate ESG performance (ESG) is also positively associated with generative AI governance (GAI).

(3) Adjusting the Sample Period

Taking into account the huge influence of both the stock market collapse of 2015 and the global coronavirus outbreak in 2020 on the economy, along with delayed economic policies, sample data in the periods 2015-2016 and 2020-2021 might have been affected by the extreme state of the economy. It would create disturbance for the whole sample. Thus, this study excludes the sample data of these periods. As a result, regression output, as shown in Column (3) of Table 2, shows the positive correlation between corporate ESG performance (ESG) and generative AI governance (GAI).

(4) Adding Provincial Fixed Effects

Due to China's large land area, provincial differences in policy regulations, economic conditions, and other issues, companies have varying perspectives on ESG performance as well as the cost that must be borne by enterprises when obtaining financing from the stock market in different provinces. For the above reasons, the current study will consider provincial fixed effects into the research, as seen in the fourth column in Table 2 below. After incorporating provincial fixed effects, a significant positive association was identified between corporate ESG performance (ESG) and generative AI governance (GAI).

Table 2: Robustness verification analysis

Variable	(1)Replace the explanatory variable GAI	(2)Replace the explained variable GAI	(3)Adjust the sample interval GAI	(4) Increase the provincial fixed effect GAI
ESG	0.105*** (2.446)	0.133** (2.173)	0.149** (2.042)	0.209*** (3.217)
Lev	-0.021** (-8.211)	-0.014*** (-5.175)	-0.026*** (-6.425)	-0.021*** (-7.346)
Top1	0.127*** (8.071)	0.118*** (4.295)	0.117*** (4.344)	0.134*** (6.339)
ROA	0.006* (1.835)	0.008** (0.248)	0.009** (0.326)	0.004** (0.728)
BM	0.123** (1.423)	0.282** (1.004)	0.344** (0.908)	0.507** (1.111)
Big4	0.401** (2.004)	0.411** (2.092)	0.247** (1.412)	0.351** (0.945)
FA	0.459** (2.723)	0.182** (2.224)	0.154** (2.008)	0.433** (2.147)
Size	0.004*** (4.083)	0.004*** (3.216)	0.009*** (5.401)	0.006*** (4.265)
Constant	0.048*** (5.491)	0.51*** (6.211)	0.016 (1.261)	0.032*** (4.206)
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Province FE	No	No	No	No
Observations	12969	12969	12969	12969
Adjusted R-squared	0.249	0.226	0.304	0.035

4.3.2 Mediating Effect Analysis

In this context, according to the above empirical model, the current research explores the mediating role of enterprise life cycle (ELC) in the correlation between corporate ESG performance (ESG) and Generative AI Governance (GAI). The results of the mediation effect test are shown in Table 3 below. Step 1: According to this model, the relationship between corporate ESG performance (ESG) and generative AI governance (GAI) was studied. The results of the regression analysis are shown in the first column in Table 3. Step 2: In accordance with this model, we explored the connection between ESG and the ELC of the company. The regression analysis results are displayed in Column (2) of Table 3. The coefficient for the connection between ESG and the life cycle of the company (ELC) is 4.278, which is positively significant at the 1% level. This means that good ESG performance of the company contributes to extending the company's life cycle (ELC). Step 3: According to this model, we evaluated the mediating role of the corporate life cycle (ELC). The regression analysis results are displayed in Column (3) of Table 3. Specifically, there is a positively significant correlation between ESG and GAI (at the 1% level), while the correlation between ELC and GAI is also positively significant at the 1% level. Therefore, it can be stated that the mediating role of the corporate life cycle (ELC) between ESG and GAI was confirmed, and research hypothesis H3 was supported.

Table 3: The analysis results of the mediating effect test

Variable	(1)GAI	(2)ELC	(3)GAI
ESG	0.218*** (3.298)	4.278*** (5.499)	0.209** (3.104)
ELC			0.006*** (4.231)
Lev	-0.018** (-8.126)	-0.308*** (-9.983)	-0.017*** (-6.275)
Top1	0.136*** (6.363)	2.061*** (9.164)	0.126*** (7.102)
ROA	0.004* (1.273)	0.018 (0.452)	0.039** (0.118)
BM	0.008** (2.274)	0.026** (1.171)	0.014** (2.236)
Big4	0.016*** (7.251)	0.004 (0.126)	0.004** (7.249)
FA	0.006* (1.392)	0.405*** (9.353)	0.002*** (2.457)
Size	0.009*** (4.242)	0.341 (52.496)	0.008*** (6.052)
Constant	0.059*** (4.718)	8.048 (50.211)	0.012 (1.184)
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Observations	12969	12969	12969
Adjusted R-squared	0.248	0.693	0.249

4.3.3 Moderation Effect Analysis

Using the model outlined above, we will now analyze the impact of industry classification (IC) on the link between corporate ESG performance (ESG) and generative AI governance (GAI). Moderation results for our study are provided in Table 4. First, the correlation between corporate ESG performance (ESG) and generative AI governance (GAI) is positively significant at a regression coefficient of 0.127 as provided in the first column of Table 4. The second column of Table 4 shows that with the moderating influence of industry classification (IC), there exists a significant positive correlation between corporate ESG performance (ESG) and generative AI governance (GAI) at a regression coefficient of 0.108. This confirms the hypothesis of moderating impact of industry classification (IC) on the link between corporate ESG performance (ESG) and generative AI governance (GAI), thereby validating Hypothesis H4.

Table 4: Results of the moderating effect analysis

Variable	(1)GAI	(2)ELC
ESG	0.127*** (0.031)	0.138*** (0.032)
IC		0.108*** (0.053)
Lev	-1.093** (-0.818)	-1.438*** (-0.826)
Top1	0.028*** (0.0019)	0.018*** (0.0019)
ROA	0.0017* (0.009)	0.018* (0.452)
BM	0.008** (2.274)	0.014** (0.138)
Big4	0.521*** (0.142)	0.541*** (0.141)
FA	0.519* (0.026)	0.519*** (0.028)
Size	0.104*** (1.312)	0.231*** (1.093)
Constant	11.405*** (0.451)	11.463*** (0.454)
Year FE	Yes	Yes
Industry FE	Yes	Yes
Observations	12969	12969
Adjusted R-squared	0.648	0.647

5 Conclusion

Based on existing literature, there are four hypotheses to be examined, and sample firms and data sources have been selected. Then, explanatory variables, dependent variables, mediating variables, control variables, and moderating variables will be established. Based on this information, the regression model is then set up. Finally, through this model, the bidirectional association between ESG performance of firms (ESG) and Generative AI Governance (GAI) is analyzed from the institutional theory perspective. If we do not take into account other elements, there is a significant positive bidirectional association between ESG performance of firms (ESG) and Generative AI Governance (GAI), verifying hypotheses H1 and H2. By changing the method for measuring explanatory and dependent variables, we can find that there is still a significant positive correlation between ESG and GAI. When adding industry classification (IC) into our original analysis framework, we can find that there is a significant positive correlation between corporate ESG performance (ESG) and generative AI governance (GAI). Therefore, it proves the mediating effect of corporate life cycle (ELC) on the correlation between ESG and GAI. That is to say, the mediating hypothesis H3 is proven to be true. Also, industry classification (IC) is positively correlated with the bidirectional association between ESG and GAI with a regression coefficient of 0.108 (0.053).

Acknowledgements

This work was supported by Anhui Philosophy and Social Science Planning Project of Research on the Relationship between Environmental Protection Input and Corporate Value of Listed Companies (AHSKQ2020D75).

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