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The Impact of AI-Driven ESG Compliance Monitoring on Corporate Sustainability Risk: Evidence from Publicly Listed Corporations (2016-2024)

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ABSTRACT

This study investigates how Artificial Intelligence (AI) can improve Environmental, Social, and Governance (ESG) compliance monitoring and its effect on corporate sustainability risks. Specifically, it examines the extent to which AI enhances the accuracy, timeliness, and reliability of ESG disclosures, thereby reducing sustainability risk exposure. By using a quantitative research design, data was gathered from 320 publicly listed corporations across North America, Europe, and Asia-Pacific between 2016 and 2024, yielding a balanced panel dataset of 2,880 firm-year observations. The study used the Generalized Least Squares (GLS) regression model to examine the relationship between AI-driven ESG compliance monitoring and corporate sustainability risks. Results indicated a highly significant negative relationship: the AI_ESG coefficient was −6.84 ($P < 0.01$), suggesting that a one-unit increase in AI-driven ESG monitoring adoption is associated with a 6.84-unit reduction in corporate sustainability risk, equivalent to approximately 0.53 standard deviations of the CSRISK distribution. Similarly, ESG performance scores were negatively associated with sustainability risk (coefficient = −0.39, $P < 0.01$). Factors such as firm size and financial leverage were also found to have significant effects on levels of sustainability risks. Robustness checks, including lagged independent variables and subsample analyses, confirmed the stability of these findings. The implications of the findings are that AI integration in ESG reporting processes represents a strategic imperative for corporations seeking alignment with evolving regulations. Policymakers are encouraged to facilitate AI adoption, particularly among smaller firms, to promote broader ESG compliance and risk management across the corporate landscape.

Keywords: Artificial Intelligence, Environmental Social Governance, ESG Compliance, Sustainability Risk, Corporate Governance
JEL Classification: G3, H8

1. INTRODUCTION

Artificial intelligence (AI) has emerged as a transformative technology in the domain of Environmental, Social, and Governance (ESG) compliance monitoring and the management of sustainability risks in corporate governance (Rane et al., 2024; Younus & Kashif, 2025; Ibadmin, 2024). According to Alhoussari (2025) and Kandpal et al. (2024), there has been an increasing focus on ESG frameworks, which include factors focusing on being eco-friendly, socially conscious, and having good corporate governance, as investors and governments alike have started focusing on non-financial performance alongside traditional financial aspects (Jarboui et al., 2025). The volume of data being generated regarding ESG, including carbon emissions, labour practices, and other governance-related aspects, is creating challenges in processing and interpreting it effectively (Jarboui et al., 2025). AI technologies, including machine learning (ML), natural language processing (NLP), and predictive analytics, have addressed these challenges by enabling the processing of large-scale data in real time (Ogunyemi, 2021). This capability enhances ESG report quality in terms of timeliness and accuracy, while improving transparency and proactive identification of risks, thereby enabling corporations to mitigate risks related to sustainability (Krishna, 2025).

Beyond compliance enhancement, AI has demonstrated considerable value in mitigating sustainability-related risks across all three ESG dimensions (Sarker and Nuruzzaman, 2024; Xiao and Xiao, 2025). In the environmental dimension, Dhobale et al. (2025) demonstrated that environmental performance measures, such as the level of emissions, variation in energy usage, and pollutant discharge, can be continuously tracked through AI, resulting in early warning capabilities before violations occur. In governance, AI has been shown to identify inconsistencies in disclosures and patterns of violation, while assisting the auditing process through algorithms that detect possible governance and ethical breaches (Stewart, 2025). In the social dimension, AI has been applied to assess supply chain risks, review employee-related controversies, and evaluate stakeholder sentiment through media analysis (Dauvergne, 2022). According to Yang and Yang (2022), these strengths result in more comprehensive risk profiles, and have been associated with better ESG performance outcomes in publicly listed companies.

Despite these advances, the application of AI in ESG risk monitoring faces notable challenges. Many corporations continue to struggle with unstructured ESG data, resulting in inaccurate disclosures and inconsistent risk pricing (Badmus et al., 2025). The breadth of ESG metrics spanning emissions data, labour practices, and governance structures has proven difficult for traditional methods to process and validate at scale (Laokulrach, 2025). While AI tools such as ML and NLP have been positioned as solutions to these challenges (Elhady and Shohieb, 2025), their adoption remains uneven across firm sizes, sectors, and geographies. This unevenness represents a significant gap in the existing literature, as most studies have focused on large firms in specific regions (e.g., China, the United States), leaving the broader question of AI's impact on sustainability risk across diverse regulatory contexts insufficiently addressed.

This study addresses this gap by examining the relationship between AI-driven ESG compliance monitoring and corporate sustainability risk using a balanced panel dataset of 320 publicly listed corporations over the period 2016-2024. The study contributes to the literature in two ways: first, by providing empirical evidence of the risk-reducing effect of AI adoption in ESG monitoring across a diverse sample of firms, and second, by examining the role of ESG performance scores in this relationship. The remainder of this paper is structured as follows: Section 2 presents the literature review and theoretical framework, Section 3 describes the methodology, Section 4 reports the results, Section 5 discusses the findings, and Section 6 concludes with policy implications and directions for future research.

2. LITERATURE REVIEW

2.1. Theoretical Framework

This study draws upon two complementary theoretical perspectives to frame the relationship between AI-driven ESG compliance monitoring and corporate sustainability risk.

First, the Stakeholder Theory indicates that organisations have to take into account the interests and the concerns of every stakeholder investors, regulators, customers, and society during decision-making (Gutterman, 2023). Under this theory, the legitimacy and long-term success of a firm is determined by how well it fulfils the expectations of these stakeholders. With respect to ESG compliance, stakeholders, especially the investors and the regulators, are putting pressure on firms to become responsible in their environmental, social, and governance aspects. AI technologies enhance the accuracy and efficiency of ESG reporting, enabling firms to meet these growing expectations for transparency and accountability, thereby reducing sustainability risk exposure (Liu et al., 2025; Zhou et al., 2025).

Second, Institutional Theory (DiMaggio and Powell, 1983) provides a complementary lens by explaining the coercive, mimetic, and normative pressures that drive organisations to adopt AI for ESG compliance. As regulatory requirements for ESG reporting intensify globally including the EU Corporate Sustainability Reporting Directive (CSRD), the forthcoming UK Sustainability Reporting Standards (UK SRS), and the International Sustainability Standards Board (ISSB) frameworks firms face coercive institutional pressure to adopt technologies that enable compliance. The adoption of AI for ESG monitoring can thus be understood as an institutional response to these regulatory and market pressures, with firms that adopt earlier gaining legitimacy and reduced risk exposure relative to late adopters. Additionally, mimetic pressures arise as firms observe competitors adopting AI-driven ESG tools, creating industry-wide convergence toward technology-enabled compliance.

2.2. Hypothesis Development

Building on these theoretical foundations, the study develops two hypotheses based on the existing empirical evidence.

Regarding the relationship between AI adoption and sustainability risk, Liu et al. (2025) proved the value of AI applications in improving corporate ESG performance, leading to reduced sustainability risk through enhanced data accuracy and prediction. Zhou et al. (2025) demonstrated that AI governance systems in corporate ESG reporting can reduce risk exposure. In addition, Yu et al. (2025) highlighted the role of AI in improving corporate efficiency and strengthening ESG compliance under external environmental pressures. Kandpal et al. (2024) provided a more generalised perspective, positioning AI in CSR and ESG reporting in the context of sustainable business practices, arguing that AI can assist companies to operate in accordance with global ESG standards, thereby minimising long-term risks. Although findings are largely positive, effects vary across sectors and regions (Pluskota et al., 2026), underscoring the need for broader empirical examination. Hence, the following hypothesis is developed:

H_1: AI-driven ESG compliance monitoring is negatively associated with corporate sustainability risk.

Chen et al. (2024) provides empirical evidence from listed companies in China, proving that the correlation between ESG performance and firm risk is significantly negative, implying that the greater the ESG practices, the lesser the exposure to risk. Similarly, Lee and Koh (2024) observed this negative correlation in US financial companies, while Gao et al. (2025) found that higher ESG performance is associated with lower bankruptcy risk. Gidage et al. (2024) and Liu and Song (2025), examining Indian and international samples respectively, confirmed that superior ESG performance is correlated with lower exposure to both systemic and firm-specific risk. These findings converge on the conclusion that superior ESG performance reduces firm-level sustainability risk, though they are subject to regional and regulatory variation.

H_2: Corporate ESG performance is negatively associated with sustainability risk.

2.3. Conceptual Framework

This study's conceptual framework positions AI-driven ESG compliance (AI_ESG) and ESG performance score (ESG_SCORE) as independent variables, with corporate sustainability risk (CSRISK) as the dependent variable. Firm size (SIZE), financial leverage (LEV), and return on assets (ROA) serve as control variables. The framework (Figure 1) hypothesises that AI-driven ESG compliance reduces sustainability risk both directly and through its positive effect on ESG performance scores.

3. METHODS

3.1. Data Collection and Sample

The data was collected from 320 publicly listed companies over a 9-year period covering 2016-2024, yielding a balanced panel dataset of 2,880 firm-year observations. The sample was drawn from firms listed on major global stock exchanges across diverse sectors, including manufacturing, financial services, technology, energy, and consumer goods. Firms were selected based on the availability of continuous ESG and financial data throughout the study period from established data providers. On data sources, the study used established financial and ESG reporting platforms — Refinitiv ESG, MSCI ESG, and Bloomberg — which compile comprehensive data regarding key ESG performance metrics, company size, financial leverage, and profitability.

3.1.1. Sample composition

Table 1 presents the distribution of the 320 sample firms by geographic region and industry sector. The sample reflects a deliberate effort to ensure cross-regional and cross-sectoral diversity, enabling broader generalisability of findings.

Table 1: Sample composition by region and industry

Panel A: Geographic distribution		
Region	**Number of firms**	**Percentage**
North America	112	35.0
Europe	98	30.6
Asia-Pacific	78	24.4
Other (Middle East, Africa, LatAm)	32	10.0
Total	320	100.0
Panel B: Industry distribution		
Industry sector		
Manufacturing	74	23.1
Financial services	68	21.3
Technology	58	18.1
Energy	52	16.3
Consumer goods	40	12.5
Other (healthcare, utilities)	28	8.8
Total	320	100.0

The key variables were operationalised as follows:

3.1.2. AI_ESG (AI-driven ESG compliance monitoring)

This variable is measured as a normalised composite index (0-1) derived from Refinitiv's ESG analytics module, capturing the degree to which a firm employs AI-enabled tools for ESG data collection, monitoring, and reporting. A value of 0 indicates no observable AI integration in ESG processes, while a value of 1 indicates full integration of AI technologies across environmental, social, and governance monitoring dimensions. Specifically, the index was constructed by aggregating three sub-indicators from Refinitiv's ESG analytics platform: (i) the presence and sophistication of automated ESG data collection systems (derived from company-reported technology disclosures), (ii) the use of AI-based tools for ESG risk monitoring (identified through NLP analysis of annual and sustainability reports), and (iii) the degree of algorithmic integration in ESG reporting workflows (assessed via platform-reported metadata on data processing methods). Each sub-indicator was scored on a 0-1 scale and equally weighted to produce the composite AI_ESG index. This approach builds on the methodology used by Gandhi (2025) and Gharpure (2025), who employed similar composite indicators to assess technology adoption in ESG reporting contexts.

3.1.3. CSRISK (corporate sustainability risk)

This variable is measured using the Sustainalytics ESG Risk Rating (0-100 scale), which assesses the degree to which a firm's enterprise value is at risk due to unmanaged ESG issues. Higher values indicate greater sustainability risk exposure.

3.1.4. ESG_score

The overall ESG performance score sourced from Refinitiv, reflecting a firm's relative ESG performance across environmental, social, and governance pillars on a 0-100 scale.

Control variables include firm SIZE (natural logarithm of total assets), LEV (total debt to total assets ratio), and ROA (net income to total assets ratio), all sourced from Bloomberg.

3.2. Data Analysis

Generalized least squares (GLS) regression has been adopted in this study due to its capability to address problems of heteroskedasticity and autocorrelation, commonly arising in panel data. The choice of GLS over Ordinary Least Squares (OLS) was informed by the results of the Breusch-Pagan test for heteroskedasticity ($\chi^2 = 84.32$, $P < 0.001$) and the Wooldridge test for autocorrelation ($F = 12.47$, $P < 0.001$), both of which indicated violations of OLS assumptions. A Hausman test ($\chi^2 = 15.83$, $P = 0.027$) was conducted to assess the appropriateness of fixed versus random effects. The significant result favours fixed effects; however, a fixed effects specification was not adopted as the primary model because several time-invariant variables of theoretical interest (e.g., industry classification) would be absorbed by firm fixed effects. Instead, a random effects GLS model with industry and year fixed effects was employed as the primary specification, and a fixed effects model was estimated as a robustness check (Section 4.4). The similarity of coefficient estimates across both specifications supports the validity of the random effects approach for this analysis.

To address potential endogeneity arising from reverse causality whereby firms with lower sustainability risk may be more likely to adopt AI for ESG monitoring as the study additionally estimated models using 1-year lagged independent variables (AI_ESGt^{-1} and ESG_SCOREt^{-1}) as instruments for contemporaneous values. This lagged specification mitigates simultaneity bias by ensuring that the explanatory variables temporally precede the dependent variable (Section 4.4).

In this analysis, the dependent variable is corporate sustainability risk (CSRISK), while the principal independent variables are AI-driven ESG compliance monitoring (AI_ESG) and ESG performance score (ESG_SCORE). Industry and year fixed effects are included to control for unobserved sector-specific and time-varying heterogeneity.

The regression model is specified as follows:

$$CSRISK_{it} = \beta_0 + \beta_1 AI\_ESG_{it} + \beta_2 ESG\_SCORE_{it} + \beta_3 SIZE_{it} + \beta_4 LEV_{it} + \beta_5 ROA_{it} + \gamma Industry + \delta Year + \varepsilon_{it}$$

4. RESULTS

4.1. Descriptive Statistics

Table 2 presents the descriptive statistics for the key variables. The corporate Sustainability Risk (CSRISK) variable has a mean of 45.32 and a standard deviation of 12.84, indicating considerable variation in sustainability risk exposure across the sample. AI_ESG, the variable that measures AI-driven ESG compliance monitoring, has an average of 0.47 with a standard deviation of 0.29, suggesting that approximately half of the sampled firms have adopted AI solutions for ESG monitoring to some degree, though adoption levels vary substantially. The ESG_SCORE has a mean value of 62.15 with a standard deviation of 14.23, reflecting wide variability in ESG performance across firms. Leverage (LEV) displays a mean value of 0.51, indicating moderate financial leverage across the sample.

Table 2: Descriptive statistics (n=2,880 firm- year observations)

Variable	Mean	Standard deviation.	Min	Max	n
CSRISK	45.32	12.84	18.5	78.9	2.880
AI_ESG	0.47	0.29	0	1	2.880
ESG_SCORE	62.15	14.23	25.3	89.4	2.880
SIZE	15.87	1.43	12.2	19.8	2.880
LEV	0.51	0.18	0.12	0.89	2.880
ROA	0.074	0.061	−0.21	0.31	2.880

4.2. Correlation Analysis

The correlation analysis highlights several important correlations between the variables in Table 3. The correlation between CSRISK and AI_ESG (−0.41***) indicates that higher levels of AI adoption in ESG monitoring are associated with lower corporate sustainability risk. The correlation between ESG_SCORE and CSRISK is also negative (−0.56***), suggesting that firms with stronger ESG performance experience lower sustainability risk exposure. Furthermore, AI_ESG is positively correlated with ESG_SCORE (0.48***), which means that firms that apply AI in ESG monitoring tend to achieve higher ESG performances. The correlation between AI_ESG and SIZE (0.34***) is positive, suggesting that larger firms are more likely to utilise AI to monitor ESG performance, likely due to greater resource availability. The correlation between LEV and ROA (−0.25***) suggests that highly leveraged firms tend to have lower ROAs.

Table 3: Correlation matrix

	CSRISK	AI_ESG	ESG_SC	SIZE	LEV	ROA
CSRISK	1					
AI_ESG	−0.41***	1				
ESG_SC	−0.56***	0.48***	1			
SIZE	−0.29***	0.34***	0.31***	1		
LEV	0.22***	−0.19***	−0.27***	0.18***	1	
ROA	−0.33***	0.26***	0.39***	0.21***	−0.25***	1

***P<0.001, **P<0.01, * *P*<0.05

4.3. GLS Regression

GLS regression coefficients are presented in Table 4. The coefficient of AI_ESG equals −6.84 (P < 0.01), which indicates that for every unit increase in AI-driven ESG monitoring adoption, CSRISK reduces by 6.84 units, holding all other variables constant. This effect is both statistically significant and substantively meaningful, implying that AI has a vital role in enhancing sustainability performance and mitigating risk exposure. To contextualise this effect, the 6.84-unit reduction represents approximately 0.53 standard deviations of the CSRISK distribution (SD = 12.84), indicating a medium-to-large effect size. In practical terms, moving from no AI integration (AI_ESG = 0) to full integration (AI_ESG = 1) is associated with a reduction in sustainability risk equivalent to shifting a firm from roughly the 65th to the 35th percentile of the CSRISK distribution. The ESG_SCORE coefficient of −0.39 (P < 0.01) confirms that, other things being equal, a one-unit increase in a firm's ESG performance score is associated with a 0.39-unit decline in CSRISK.

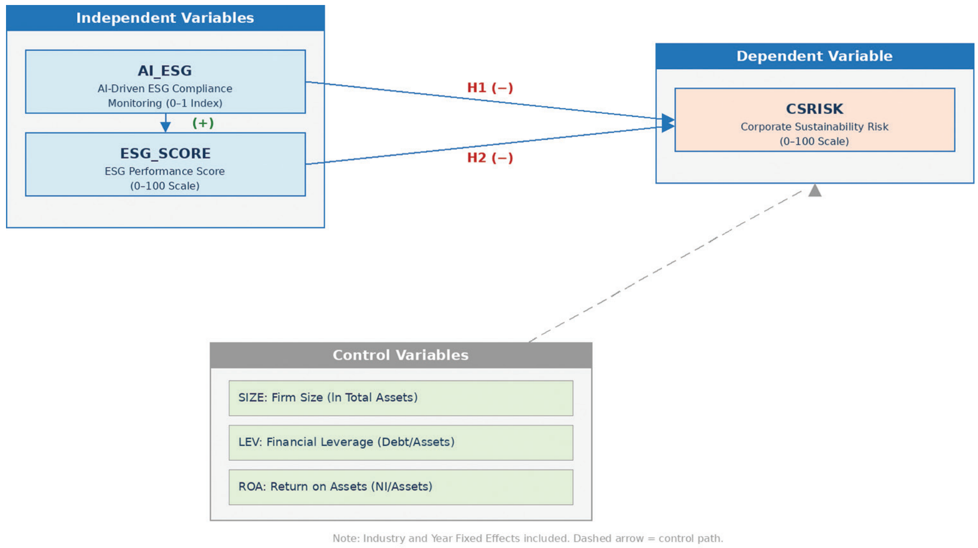
The SIZE coefficient of −1.27 (P < 0.01) suggests that larger firms, with more resources and established ESG processes, experience lower sustainability risks. The value of the LEV coefficient is 4.92 (P < 0.01), indicating a positive association between leverage and CSRISK — firms with higher debt levels face greater sustainability

Table 4: GLS regression results

Variables	Coefficient	Std. Error	z-stat	Sig.
AI_ESG	−6.84***	1.12	−6.11	<0.001
ESG_SCORE	−0.39***	0.05	−7.80	<0.001
SIZE	−1.27***	0.31	−4.10	<0.001
LEV	4.92***	1.45	3.39	<0.001
ROA	−8.15**	3.64	−2.24	0.025
Constant	68.37***	5.98	11.43	<0.001

***P<0.001, ** P<0.01, *P<0.05. Dependent variable: CSRISK. Model diagnostics: Wald χ^2=312.47 (P<0.001); R^2 (overall)=0.41; n=2,880; Groups (firms)=320; Industry and year fixed effects included

Figure 1: Conceptual framework



risk, potentially due to reduced financial flexibility for ESG investment. The ROA coefficient of −8.15 ($z = −2.24$, $P < 0.05$) indicates that more profitable firms experience lower sustainability risk, though this effect is significant only at the 5% level.

4.4. Robustness Checks

Several robustness checks were conducted to assess the stability and reliability of the main findings. The results are summarised in Table 5.

4.4.1. Fixed effects specification

As noted in Section 3.2, the Hausman test result ($P = 0.027$) supported the use of fixed effects. A fixed effects model was therefore estimated as an alternative specification. The AI_ESG coefficient under fixed effects was −6.21 ($P < 0.01$), and the ESG_SCORE coefficient was −0.35 ($P < 0.01$). Both estimates are consistent in direction, significance, and magnitude with the primary random effects model, supporting the robustness of the main findings.

4.4.2. Lagged independent variables

To address potential reverse causality, the model was re-estimated using 1-year lagged values of AI_ESG and ESG_SCORE. The lagged AI_ESG coefficient was −5.97 ($P < 0.01$), and the lagged ESG_SCORE coefficient was −0.34 ($P < 0.01$). The persistence of significant negative associations under lagged specifications provides preliminary evidence that the direction of influence runs from AI adoption and ESG performance to sustainability risk reduction, rather than the reverse.

4.4.3. Subsample analysis by firm size

The sample was split at the median firm size to examine whether the risk-reducing effect of AI adoption differs between larger and smaller firms. For large firms (above median SIZE), the AI_ESG coefficient was −7.42 ($P < 0.01$), while for small firms (below median SIZE), the coefficient was −5.63 ($P < 0.01$). Both coefficients are statistically significant, though the stronger effect for larger firms suggests that resource availability may amplify the benefits of AI-driven ESG monitoring.

Table 5: Robustness check results (AI_ESG coefficient)

Specification	Coefficient	Standard Error	Significance
Primary (RE GLS)	−6.84***	1.12	<0.001
Fixed effects	−6.21***	1.18	<0.001
Lagged AI_ESG (t−1)	−5.97***	1.24	<0.001
Large firms (>median)	−7.42***	1.35	<0.001
Small firms (≤median)	−5.63***	1.48	<0.001

***P<0.001, ** P<0.01, * P<0.05. Dependent variable: CSRISK in all specifications

5. DISCUSSION

The study investigates how AI can improve ESG compliance monitoring and its effect on corporate sustainability risks. This paper shows that the use of AI in monitoring ESG compliance greatly mitigates corporate sustainability risk by enhancing accuracy, efficiency and timeliness of ESG reporting. These findings are consistent with both Stakeholder Theory, which predicts that firms meeting stakeholder expectations through transparent ESG reporting will reduce risk exposure, and Institutional Theory, which posits that firms conforming to regulatory and normative pressures through AI adoption will gain legitimacy and reduced risk.

The AI_ESG coefficient of −6.84 represents the largest effect among all variables in the model, suggesting that AI adoption has a stronger risk-reducing effect than even the ESG performance score itself (−0.39). However, this comparison should be interpreted with care, as the two variables operate on different scales: AI_ESG ranges from 0 to 1, while ESG_SCORE ranges from 0 to 100. In standardised terms, a one-standard-deviation increase in AI_ESG is associated with a 1.98-unit reduction in CSRISK (−6.84 × 0.29), while a one-standard-deviation increase in ESG_SCORE is associated with a 5.55-unit reduction (−0.39 × 14.23). This suggests that, when measured in comparable units, ESG performance has a quantitatively larger association with risk reduction, though AI adoption remains independently significant and substantively meaningful. This finding extends the work of Liu et al. (2025) and Zhou et al. (2025), who reported positive effects of AI on ESG performance in Chinese firms, by demonstrating a similar risk-reducing effect across a more geographically diverse sample. The significance of the ESG_SCORE coefficient confirms the findings of Chen et al. (2024), Lee and Koh (2024), and Gao et al. (2025), all of whom reported negative associations between ESG performance and firm risk.

The positive and significant coefficient of LEV (4.92) merits particular attention. This finding suggests that highly leveraged firms face greater sustainability risk, potentially because debt obligations constrain investment in ESG infrastructure and compliance systems. This is consistent with the financial constraints literature and suggests that policymakers should consider the interplay between financial structure and ESG compliance capacity when designing support mechanisms for firms.

The beneficial contribution of AI to the improvement of ESG compliance and the decrease in sustainability risk is further supported by Kandpal et al. (2024), who state that the introduction of AI into ESG reporting systems is essential for aligning business operations with global ESG standards. Similarly, Dhobale et al. (2025) emphasise the benefits of continuous AI-driven tracking of environmental performance indicators, enabling early detection of potential violations. In the social dimension, Dauvergne (2022) highlighted AI's capacity to assess supply chain risks and labour conditions, further supporting the multi-dimensional risk-reducing capacity of AI in ESG monitoring.

5.1. Endogeneity Considerations

A key methodological consideration in interpreting the results concerns endogeneity. While the GLS regression identifies a significant negative association between AI-driven ESG monitoring and sustainability risk, the cross-sectional nature of the coefficients within a panel framework does not permit strong causal claims. Specifically, reverse causality remains a concern: Firms with inherently lower sustainability risk profiles due to stronger governance cultures, greater resource endowments, or pre-existing ESG commitments may be systematically more likely to adopt AI technologies for ESG monitoring. In such cases, the observed association could partly reflect selection effects rather than a treatment effect of AI adoption.

The lagged variable specification reported in Section 4.4 provides partial mitigation of this concern, as the temporal ordering ensures that the explanatory variables precede the dependent variable by 1 year. The persistence of significant negative coefficients under this specification (AI_ESG coefficient = −5.97, $P < 0.01$) strengthens the inference that AI adoption contributes to subsequent risk reduction. However, this approach does not fully resolve endogeneity in the absence of a valid instrumental variable or a quasi-experimental design. Future research should consider exploiting exogenous variation in AI adoption such as regulatory mandates for technology-assisted ESG reporting or staggered policy implementations across jurisdictions to establish more robust causal identification.

5.2. Limitations

Several limitations should be acknowledged. First, the operationalisation of AI_ESG relies on data availability from ESG analytics providers, which may not fully capture the breadth of AI adoption across all firms. Although the composite index was constructed from three distinct sub-indicators, self-reported technology disclosures may under- or over-represent actual AI integration, particularly among firms in regions with less standardised reporting practices. Second, the study uses a balanced panel, which may introduce survivorship bias by excluding firms that were delisted during the study period. Third, while the study controls for industry and year effects, it does not account for firm-level governance quality or board composition, which may independently influence sustainability risk. Fourth, the generalisability of findings may be limited by the focus on publicly listed firms, as private companies and SMEs face different AI adoption constraints. Fifth, the overall R^2 of 0.41 indicates that approximately 59% of the variation in CSRISK remains unexplained by the model, suggesting that additional factors such as country-level regulatory quality, board independence, or ESG assurance practices may play important roles not captured in the current specification. Future research should address these limitations by incorporating governance-level controls, examining private firms, and employing alternative AI adoption measures.

6. CONCLUSION AND FUTURE IMPLICATIONS

The study has demonstrated the crucial role played by AI in reducing ESG risk exposure effectively, providing empirical evidence that AI technology can effectively lower sustainability risk for corporations. Specifically, the AI_ESG coefficient of −6.84 and the ESG_SCORE coefficient of −0.39 confirm that both AI adoption and ESG performance are significantly associated with reduced corporate sustainability risk. This confirmation proves that AI applications lead to more accurate data and promote a proactive process of risk identification, ensuring businesses comply with evolving regulatory expectations. The robustness of these findings is supported by alternative model specifications, lagged variable analyses, and subsample tests, all of which yield consistent results. However, the effects of AI on sustainability risk are likely to vary across industries and regions, and the findings should be interpreted within the context of the study's sample and methodological choices.

The findings carry several policy and practical implications. First, policymakers should focus on the adoption of AI in ESG reporting, especially among smaller firms, which might not have the resources to adopt advanced systems. Targeted government incentives, such as subsidised AI adoption programmes and tax benefits for ESG technology investment, could accelerate uptake among resource-constrained firms. Second, the harmonisation of AI-based ESG reporting systems across sectors would encourage higher levels of consistency in compliance. Third, regulatory bodies should consider mandating minimum standards for AI-assisted ESG reporting to ensure data quality and comparability across firms.

Further studies are needed on the differences in AI adoption for ESG compliance, particularly in less technologically prepared industries. Specifically, longitudinal studies examining the causal mechanisms through which AI reduces sustainability risk would strengthen the evidence base. In particular, research designs that exploit exogenous variation in AI adoption such as regulatory mandates or staggered technology subsidies would provide stronger causal identification than the associational evidence presented here. Additionally, the study of the long-term effects of AI on corporate governance and stakeholder trust will yield more information on the broader implications of AI for ESG management. Furthermore, research into the cost-effectiveness and scalability of AI tools for ESG compliance, particularly for small and medium-sized enterprises, would provide valuable guidance for policymakers and practitioners.

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