

From Technology to Sustainability: Unraveling AI's Role in Enhancing ESG Metrics

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Abstract: This study explores the role of digital transformation in advancing corporate responsibility. Addressing this through the lens of resource dependency theory, we analyse the link between Artificial Intelligence (AI) development and Environmental, Social, and Governance (ESG) performance in publicly traded companies. After controlling for endogeneity via instrumental variables, our data reveals that AI acts as a potent catalyst for ESG enhancement, particularly within non-high-tech industries and developing economic zones. The study highlights that the benefits of AI are not uniform; rather, they depend heavily on the economic context. These insights challenge a one-size-fits-all approach, advocating instead for tailored AI strategies. The findings provide actionable guidance for practitioners and regulators seeking to leverage technology to meet sustainability goals.

Keywords: AI; ESG Performance; Resource Dependency Theory

1. Introduction

ESG criteria have cemented their status as a cornerstone of sustainable development within the modern business landscape ^[1]. By capturing a firm's dedication to non-financial stewardship, ESG ratings now heavily influence capital allocation and stakeholder confidence ^[2]. As organizations face pressure to harmonize operations with broader sustainability goals, ESG performance stands as a critical indicator of strategic resilience. This reality demands that public companies move beyond superficial adoption, instead embedding ecological and ethical considerations into their core frameworks to ensure enduring viability and value creation ^[3].

The integration of AI offers businesses a powerful lever for transformation, driving innovation and sharpening competitive edges through superior operational efficiency ^[4]. By parsing massive datasets, AI grants leaders unprecedented clarity, streamlining decision-making in ways previously impossible ^[5]. Yet, when viewed through the lens of ESG, the impact of AI is far from binary. While it can bolster environmental stewardship and governance transparency, it carries the risk of undermining social goals if issues like workforce displacement are ignored. This duality suggests that simply adopting AI is not enough; firms must rigorously evaluate how these tools are deployed to ensure they align with, rather than erode, their sustainability mandates.

Drawing on resource dependency theory, this study investigates how AI development shapes the ESG performance of public firms, utilizing provincial AI levels as an instrumental variable to validate results across diverse economic and industrial contexts. By clarifying how technological advancements align with specific environmental, social, and governance goals, the research bridges the gap between digital strategy and sustainable practice ^[6-7]. Furthermore, applying resource dependency theory to this digital context offers a novel framework for interpreting the AI-ESG nexus, providing actionable guidance for companies striving to balance innovation with sustainability mandates ^[8].

After reviewing the prevailing literature on AI and ESG, we detail the methodology employed in this study. The analysis then moves to our empirical results, offering an interpretation of the data relevant to the fields of management and sustainability. Finally, the conclusion synthesizes these insights and highlights opportunities for future research.

2. Literature Review

2.1 Literature review about ESG

Research increasingly positions ESG performance not merely as a peripheral trend, but as a fundamental strategic imperative that drives financial value and competitive advantage. Firms with robust ESG credentials consistently demonstrate superior financial metrics, including higher profitability and market stability, while attracting a growing base of investors who recognize the long-term value of sustainable governance^[9-11]. Beyond direct financial returns, effective ESG management acts as a critical buffer against operational, legal, and reputational risks, allowing companies to navigate complex regulatory environments with greater agility^[12-13]. Furthermore, integrating these principles fosters an innovative culture, where sustainability mandates catalyze new product development and process improvements. Ultimately, as stakeholder expectations evolve, ESG has become a decisive factor in corporate success, aligning ethical responsibility with economic resilience^[2, 14-16].

Recent scholarship on the drivers of ESG performance increasingly points to digital transformation as a key catalyst. By facilitating the precise tracking and analysis of data, digitalization significantly improves the quality of ESG reporting and execution^[17]. These technological tools do not replace traditional foundations like corporate governance and stakeholder engagement; rather, they augment them, creating fresh opportunities for companies to elevate their standards. Concurrently, the complexity of global supply chains has brought cross-border collaboration and compliance into sharper focus as essential components of meeting ESG goals^[18]. Together, these insights illustrate how the antecedents of ESG are shifting to keep pace with broader technological and socio-economic changes.

2.2 Literature review about AI

Current research depicts corporate AI development as a powerful engine for transformation, offering substantial opportunities for innovation, efficiency, and competitive differentiation^[19]. By processing vast datasets, AI empowers firms to make sharper, data-driven decisions while simultaneously driving operational efficiency through automation that streamlines workflows and minimizes human error^[20-21]. This technological capability extends deeply into product development and customer relations; companies leverage AI to uncover patterns beyond human reach, fostering novel products and highly personalized client experiences^[22]. However, this rapid evolution is not without friction. As the landscape shifts, businesses must carefully navigate complex challenges regarding workforce dynamics and ethical considerations, necessitating continuous scholarly attention to fully understand AI's evolving impact on the commercial world^[23].

The integration of AI, however, is not without significant friction. Beyond the technical implementation, firms must navigate complex ethical landscapes—ranging from privacy and surveillance to decision-making autonomy—where a lack of robust governance can entrench bias and discrimination^[24]. Simultaneously, the automation of labor presents a pressing socio-economic challenge, creating an urgent need for strategies focused on workforce reskilling and transition. Despite these hurdles, the financial argument for AI remains strong. Investments in the technology are linked not only to cost reductions via efficiency but also to revenue growth derived from novel products and services, creating a distinct competitive advantage in global markets^[25]. Realizing these gains, however, requires more than just capital; it demands the strategic alignment of AI initiatives with the firm's broader vision and mission^[26]. Furthermore, the literature indicates that this impact is highly context-dependent, varying significantly across sectors—from predictive diagnostics in healthcare to algorithmic risk assessment in finance.

2.3 Hypothesis about AI and ESG

Viewed through the lens of Resource Dependence Theory (RDT), corporate AI development represents a strategic effort to manage external uncertainty by cultivating vital internal capabilities^[27]. This dynamic deeply influences ESG performance: environmentally, AI acts as a tool for superior resource stewardship, optimizing energy use and minimizing waste^[22]. The social dimension, however, presents a complex trade-off; firms must balance the benefits of personalized service against the ethical weight of job displacement and privacy concerns^[24]. Finally, while AI can sharpen governance through

data-driven transparency, it simultaneously demands rigorous ethical oversight to ensure these systems remain accountable and free from bias ^[28]. Therefore, we would like to present

Hypothesis 1: The development of artificial intelligence in publicly listed companies can enhance their ESG performance.

Drawing from resource dependency theory, which posits that organizations adapt to external environments to secure essential resources ^[29], we hypothesize that the impact of AI on ESG performance may vary based on regional development levels. In developed regions, where resources are abundant and ESG practices may already be advanced, the marginal benefit of AI on ESG might be less pronounced. Conversely, in less developed areas, where ESG practices are emerging, AI can provide significant leverage for resource acquisition and stakeholder engagement, leading to a more substantial impact on ESG performance. Thus, we propose

Hypothesis 2: The development of artificial intelligence in companies located in developed regions has a lower impact on ESG performance compared to those in less developed regions.

Resource dependency theory posits that organizations shape their strategies to secure vital resources and satisfy external stakeholders ^[30]. In high-tech industries, where AI is the engine of innovation and competitive advantage, firms tend to prioritize investments that drive technological breakthroughs over those explicitly targeting ESG goals. Consequently, AI's primary contribution in these sectors is often to innovation rather than sustainability metrics. Conversely, in non-high-tech sectors, AI is frequently adopted to streamline operations, ensure regulatory compliance, and meet societal expectations. Here, the link between AI and ESG is more direct: by optimizing efficiency and governance, AI adoption translates more readily into improved ESG performance. Thus, while high-tech firms leverage AI to maintain industry leadership, non-high-tech firms often use it to address operational and social responsibilities, creating a clearer path to higher ESG scores. Therefore, we propose

Hypothesis 3: The development of artificial intelligence in high-tech industry firms has a weaker impact on corporate ESG performance compared to non-high-tech industries.

3. Data and Model

3.1 Data

The data in this article are comprised of three main parts: First, the corporate governance structure data and financial data of publicly listed companies, primarily derived from the CSMAR database. Second, the ESG rating data of listed companies, sourced from ZhiDing Company, one of the first in China to engage in professional ESG research, focusing on sustainable investment and financing for Chinese financial institutions and sustainable development for Chinese enterprises, providing ESG data standards and research consultancy reports tailored for the Chinese market. This data is monthly and is averaged using a weighted average method to determine the annual ESG score for each company. Third, the artificial intelligence patent data of listed companies, obtained from the National Intellectual Property Administration. We identify AI patents by screening patent titles using predefined keywords, as listed in Table 1. By merging these three databases, and considering that China's ESG data mainly starts from 2014, the sample period for this study spans from 2014 to 2022.

Table 1: Listed Company Artificial Intelligence Patent Identification Keywords

Column 1	Column 2	Column 3	Column 4
Intelligent	AI	Machine Translation	Computer Vision
Human-Computer Interaction	Deep Learning	Neural Networks	Biometrics
Image Recognition	Data Mining	Feature Recognition	Speech Synthesis
Speech Recognition	Knowledge Graph	Intelligent Banking	Intelligent Insurance
Human-Machine	Intelligent Supervision	Intelligent Education	Intelligent Customer Service

Collaboration			
Intelligent Retail	Intelligent Agriculture	Intelligent Investment Advisory	Augmented Reality
Virtual Reality	Intelligent Healthcare	Smart Speaker	Intelligent Voice
Intelligent Government Affairs	Autonomous Driving	Intelligent Transportation	Convolutional Neural Networks
Voiceprint Recognition	Feature Extraction	Unmanned Driving	Smart Home
Question Answering System	Face Recognition	Business Intelligence	Intelligent Finance
Recurrent Neural Networks	Reinforcement Learning	Intelligent Agents	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	Intelligent Chip	Wearable Products
Big Data Management	Intelligent Sensors	Pattern Recognition	Edge Computing
Big Data Platform	Intelligent Computing	Intelligent Search	Internet of Things
Cloud Computing	Enhanced Intelligence	Voice Interaction	Intelligent Environmental Protection
Human-Machine Dialogue	Deep Neural Networks	Big Data Operation	Big Data

3.2 Variables

To examine the relationship between corporate artificial intelligence development and corporate ESG performance, the following explanatory variable, Independent variable, moderating variable, and control variables are involved:

Independent Variable: Corporate ESG performance (ESG), as measured by the ESG scores released by ZhiDing Company, is used to assess the company's ESG performance. To reduce heteroscedasticity, the scores are transformed using a logarithmic form. Additionally, the E score, S score, and G score released by the company are also considered separately.

Explanatory Variable: Corporate AI development (AIpatent), measured by the number of AI patents held by listed companies, is used as the metric for assessing corporate AI advancement. To mitigate heteroscedasticity, a logarithmic transformation is applied to this variable.

Moderating Variables: In line with the derived impact mechanisms, the main moderating variables include whether the company is located in a developed economic region (East, 1 for eastern regions, 0 otherwise) and whether the company operates in a high-tech industry (High-tech, 1 for yes, 0 otherwise).

Control Variables: Based on existing research, the study controls for a series of variables: Company Size (Size), measured by the logarithm of total assets; Debt Ratio (Lev), measured by the logarithm of the asset-liability ratio; Growth, represented by the growth rate of company revenue; Board, measured by the logarithm of the board size; InIndependent, represented by the proportion of independent directors, logarithmically transformed; TMTAge, the average age of the top management team, logarithmically transformed; and Mshare, the management's shareholding ratio, logarithmically transformed.

3.3 Model

To explore how AI development impacts the ESG performance of listed companies, we rely on the Generalized Estimating Equations (GEE) model as a pivotal analytical tool. This section outlines why GEE is particularly well-suited for this context, specifically when using AI patents (AIPatent) as a proxy for technological development and ESG scores to measure corporate sustainability. While the integration of AI into business operations is increasingly seen as a driver of ESG performance, analyzing this relationship requires a method that can handle the complexities of real-world data. This is where the GEE model shines. It is inherently designed to manage correlated data—a common feature in panel datasets where a single company is measured repeatedly over time. By accounting for these temporal dependencies, GEE ensures that our estimates of the AI-ESG relationship are both reliable and valid.

Beyond just handling correlation, the GEE framework offers remarkable flexibility. It accommodates various link functions and correlation structures, allowing researchers to tailor the analysis to the specific nature of the data, whether the outcomes are continuous, binary, or counts. Crucially, GEE is resilient: even if the chosen correlation structure isn't a perfect match for reality, the model still provides consistent parameter estimates. When the structure is correctly specified, the estimators are not only consistent but also efficient, yielding the smallest possible standard errors. This robustness makes GEE an ideal choice for empirical research where the true underlying correlation is often unknown.

In the context of analyzing AI's impact on ESG performance, the GEE model can be specified as follows:

$$ESG_{it} = \beta_0 + \beta_1 AIPatent_{it} + \beta_2 Control_{it} + \varepsilon_{it} \quad (1)$$

Where ESG_{it} is the ESG score of company i at time t , $AIPatent_{it}$ represents the number of AI patents, and $Control_{it}$ encompasses a vector of control variables such as company size, industry, and other relevant factors. The choice of an appropriate link function and correlation structure would be dictated by the nature of the ESG data and the research objectives.

Incorporating regional (East) and high-tech industry (High-tech) as moderating variables into the GEE model offers a nuanced perspective on how the impact of AI development on ESG performance might vary across different geographical areas and industry sectors. Here, we specify two separate moderated models.

The first model introduces a regional moderator, East, which is a binary variable indicating whether a company is located in the eastern region (East = 1 if the company is in the east, 0 otherwise). This model explores whether the relationship between AI patent development (AIPatent) and ESG performance differs between companies in the eastern region compared to those in other regions.

$$ESG_{it} = \beta_0 + \beta_1 AIPatent_{it} + \beta_2 Control_{it} + \beta_3 East_i + \beta_4 (AIPatent_{it} \times East_i) + \varepsilon_{it} \quad (2)$$

Here, β_4 captures the interaction effect between AIPatent and East, indicating how the relationship between AIPatent and ESG performance changes for companies in the eastern region.

The second model integrates High-tech as a moderating variable, where High-tech is a binary variable that denotes whether a company belongs to the high-tech industry (High-tech = 1 for high-tech industry, 0 otherwise). This model examines whether AI's impact on ESG performance is distinct within high-tech industries compared to other sectors

$$ESG_{it} = \beta_0 + \beta_1 AIPatent_{it} + \beta_2 Control_{it} + \beta_3 High_tech_i + \beta_4 (AIPatent_{it} \times High_tech_i) + \varepsilon_{it} \quad (3)$$

In this equation, β_4 signifies the interaction effect between AIPatent and High-tech, illustrating how the influence of AIPatent on ESG performance is. In both models, the interaction terms $AIPatent_{it} \times East_i$ and $AIPatent_{it} \times High_tech_i$ are key to understanding the moderating effects. A significant coefficient for β_4 in either model would suggest that the impact of AI development on ESG performance is contingent upon the company's region or industry sector. For instance, a positive and significant β_4 in the first model would imply that the positive impact of AI development on ESG performance is stronger for companies in the eastern region.

4. Results

4.1 Descriptive analysis

In this descriptive analysis of the Table 2, we focus on the relationship between the explained variable, ESG, and the explanatory variable, AI, while accounting for various control variables. The variable ESG, serving as the independent variable, has a mean value of 3.96 with a standard deviation of 0.15, ranging from 3.60 to 4.40. AI, the key independent variable, has an average of 0.42, a standard deviation of 0.85, and values that vary between 0.00 and 5.51. Its VIF of 1.05 suggests minimal multicollinearity concerns, reinforcing the variable's suitability for regression analysis.

For the control variables, Size averages 3.11 with little variation, whereas Lev shows a negative mean, suggesting potential leverage anomalies. ROA presents a modest average alongside a wide spread of values, and Growth varies significantly across observations. In terms of governance, Board and Independent represent standard measures of board size and independence. We also include TMTAge and Mshare to account for the age of the top management team and management shareholding, respectively.

Table 2: Descriptive Analysis

Variable	Obs	Mean	Std. Dev.	Min	Max	VIF
ESG	344,048	3.96	0.15	3.60	4.40	
AI	344,048	0.42	0.85	0.00	5.51	1.05
Size	344,048	3.11	0.06	2.91	3.42	1.61
Lev	344,048	-0.98	0.61	-3.64	0.66	1.43
Growth	336,740	0.25	1.77	-0.90	45.88	1.02
Board	344,024	2.12	0.21	1.39	2.89	1.70
InIndependent	344,024	3.62	0.14	2.30	4.20	1.52
TMTAge	344,036	49.64	3.25	38.86	59.92	1.24
Mshare	332,991	1.52	1.60	0.00	4.37	1.26

Table 3 summarizes the correlation coefficients between the dependent variable, ESG, and the set of explanatory and control variables, which includes AI, Size, Lev, Growth, Board, Independent, TMTAge, and Mshare. The results reveal a mix of positive and negative associations, highlighting the complex interplay between these factors. Specifically, ESG is positively correlated with AI and Size, whereas it exhibits a negative relationship with Growth and Mshare. This suggests that while certain firm characteristics may enhance ESG performance, others appear to exert a dampening effect.

The absence of extremely high correlation coefficients (close to 1 or -1) suggests that multicollinearity is likely not a significant concern for this dataset, which is crucial for ensuring the validity of any subsequent regression analysis. This is further supported by the relatively low VIF values presented in the table 1, which are all well below the commonly used threshold of 10.

Table 3: Pair-wise Correlation

VARIABLES	ESG	AIpatent	Size	Lev	Growth	Board	Independent	TMTAge	Mshare
ESG	1								
AIpatent	0.193***	1							
Size	0.484***	0.155***	1						
Lev	0.147***	0.021***	0.456***	1					
Growth	-0.044***	-0.025***	0.025***	0.029***	1				
Board	0.155***	0.027***	0.341***	0.164***	-0.002	1			
InIndependent	0.008	0.027***	-0.020***	-0.012**	-0.002	-0.547***	1		
TMTAge	0.311***	0.050***	0.381***	0.121***	-0.036***	0.244***	-0.043***	1	
Mshare	-0.154***	0.083***	-0.348***	-0.299***	0.003	-0.221***	0.056***	-0.271***	1

Note: *** p<0.01, ** p<0.05, * p<0.1

In summary, the correlations presented are reasonable and indicate a well-considered dataset that is suitable for further analysis. The relationships between variables are statistically significant and suggest that the dataset is robust for conducting a detailed correlation or regression analysis to explore the factors influencing ESG performance.

4.2 Baseline Regression

The regression analysis presented in Table 4 examines the impact of AI development on the ESG performance of publicly traded companies, differentiated into the overall ESG score and its individual components (Environmental - E, Social - S, Governance - G).

Table 4: The baseline regression between AI and ESG performance

VARIABLES	Model1	Model2	Model3	Model4	Model5
	ESG	ESG	E	S	G
AI	0.025***	0.015***	0.026***	0.019***	0.002**
	(21.66)	(13.47)	(10.51)	(11.71)	(2.21)
Size		1.547***	2.135***	1.768***	0.914***
		(66.11)	(42.70)	(47.44)	(59.50)
Lev		-0.012***	-0.001	-0.010***	-0.014***
		(-6.72)	(-0.16)	(-3.76)	(-12.27)
Growth		-0.004***	-0.005***	-0.003***	-0.002***
		(-9.73)	(-5.96)	(-6.28)	(-10.91)
Board		-0.067***	-0.165***	-0.071***	-0.002
		(-10.78)	(-11.69)	(-7.57)	(-0.56)
Independent		0.007	-0.039**	0.013	0.026***
		(0.83)	(-2.14)	(1.12)	(5.14)
TMTAge		0.008***	0.015***	0.007***	0.004***
		(25.14)	(20.27)	(13.10)	(19.63)
Mshare		-0.002***	0.004**	-0.003**	-0.002***
		(-2.70)	(2.20)	(-2.19)	(-4.00)
Constant	3.953***	-1.139***	-3.177***	-1.897***	1.089***
	(2361.47)	(-14.92)	(-19.36)	(-15.66)	(21.79)
Observations	29795	28297	28297	28297	28297
Wald Chi2	469.1***	7771.5***	3694.1***	3614.3***	5628.7***

Note: z-statistics in parentheses *** p<0.01, ** p<0.05, * p<0.1

Model 1, without control variables, shows a positive and statistically significant relationship between AI development and ESG performance (coefficient = 0.025, $p < 0.01$), indicating that as AI patenting activity increases, there is a notable improvement in ESG scores. The significance of the AI coefficient across all models suggests a consistent positive effect of AI on ESG outcomes.

Upon introducing control variables (Size, Lev, Growth, Board, Independent, TMTAge, and Mshare) in Model 2, the positive association between AI and ESG performance persists. Although the coefficient slightly attenuates to 0.015 ($p < 0.01$), it confirms that AI remains a significant predictor of

ESG outcomes even after accounting for firm-specific characteristics.

A deeper look at the ESG pillars reveals that AI's influence is not uniform. Model 3 indicates that AI has the strongest impact on the Environmental component (coefficient = 0.026, $p < 0.01$). The effect remains positive but diminishes slightly for the social dimension in Model 4 (coefficient = 0.019, $p < 0.01$), and is weakest—though still statistically significant—for the Governance aspect in Model 5 (coefficient = 0.002, $p < 0.05$).

Regarding the control variables, the results align with general expectations: Size is consistently positively correlated with ESG scores, implying that larger firms are better positioned to uphold sustainability standards. Conversely, Lev and Growth tend to show negative coefficients, suggesting that high leverage and rapid expansion may divert resources away from ESG initiatives. The impacts of Board characteristics, TMTAge, and Mshare vary, reflecting the complex and nuanced nature of internal governance mechanisms.

From the perspective of Resource-Based Theory, these findings imply that AI capabilities function as a strategic asset—valuable, rare, and difficult to imitate. By leveraging AI, firms gain a competitive edge that translates into superior ESG performance. However, the varying coefficients across the three pillars suggest that this “AI dividend” is not evenly distributed; AI technologies may address environmental and social challenges more directly than they do governance structures.

4.3 Moderate Effect Test

Table 5 explores how regional economic development moderates the relationship between AI adoption and ESG performance. The sample is divided into firms located in economically developed regions (East=1) and those in less developed areas (East=0).

For firms in developed regions (Models 1 and 2), AI exhibits a positive and statistically significant link to ESG performance. Specifically, the coefficient stands at 0.024 ($p < 0.01$) in Model 1 and adjusts to 0.013 ($p < 0.01$) in Model 2 after accounting for control variables. This slight reduction suggests that firm-specific characteristics explain a portion of the variance, yet the core positive impact of AI remains robust.

In contrast, the results for less developed regions (Models 3 and 4) reveal a stronger dynamic. Here, the coefficients for AI are higher—0.032 ($p < 0.01$) and 0.021 ($p < 0.01$), respectively—compared to their counterparts in developed areas. This indicates that AI adoption yields a more substantial boost to ESG performance in regions with lower economic development.

Regarding control variables, Size consistently correlates positively with ESG scores across all subsamples, though the effect is notably stronger in less developed regions. Lev and Growth generally show negative associations, implying that financial leverage and rapid expansion may constrain ESG efforts, with leverage being particularly detrimental in less developed areas. Board characteristics show negative coefficients, pointing to potential governance frictions, while TMTAge is positively associated with ESG across the board, highlighting the value of managerial experience.

The comparison suggests that the “AI premium” for ESG is more pronounced in less developed areas. This may be attributed to the marginal utility of technology; in regions where advanced digital infrastructure is scarce, AI serves as a critical differentiator and a powerful tool for sustainability. Conversely, in developed regions where high-tech practices are already ubiquitous, the incremental benefit of AI on ESG performance is comparatively smaller.

Table 5: The moderate effect between AI and ESG: Area

	Model1	Model2	Model3	Model4
VARIABLES	East=1	East=1	East=0	East=0
AI	0.024***	0.013***	0.032***	0.021***
	(17.91)	(10.44)	(12.58)	(8.66)
Size		1.503***		1.606***
		(54.04)		(37.19)

Lev		-0.004*		-0.032***
		(-1.73)		(-9.16)
Growth		-0.004***		-0.003***
		(-9.24)		(-4.20)
Board		-0.064***		-0.069***
		(-8.73)		(-5.87)
lnIndependent		0.010		-0.001
		(1.09)		(-0.08)
TMTAge		0.008***		0.008***
		(22.32)		(12.19)
Mshare		-0.003***		-0.001
		(-3.65)		(-0.47)
Constant	3.954***	-1.012***	3.947***	-1.314***
	(1975.54)	(-11.15)	(1324.83)	(-9.31)
Observations	21208	20222	8587	8075
Number of firmid	3456	3363	1273	1237
N	21208	20222	8587	8075
Wald Chi2	320.8***	5667.9***	158.2***	2163.1***

Note: z-statistics in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 6 extends the analysis from Table 3 by examining the moderating effect of industry type (high-tech vs. non-high-tech) on the relationship between AI development and ESG performance. The table compares the impact of AI on ESG scores across high-tech (Models 1 and 2) and non-high-tech industries (Models 3 and 4), with and without control variables.

Table 6: The moderate effect between AI and ESG: High-tech industry

VARIABLES	Model1	Model2	Model3	Model4
	Hightech=1	Hightech=1	Hightech=0	Hightech=0
AI	0.020***	0.010***	0.032***	0.020***
	(12.06)	(6.78)	(19.04)	(12.04)
Size		1.646***		1.431***
		(45.84)		(46.01)
Lev		-0.010***		-0.012***
		(-3.96)		(-4.78)
Growth		-0.004***		-0.004***
		(-6.47)		(-7.43)
Board		-0.057***		-0.068***
		(-6.43)		(-7.87)

InIndependent		0.009		0.011
		(0.74)		(1.01)
TMTAge		0.008***		0.009***
		(16.96)		(19.13)
Mshare		-0.004***		-0.001
		(-3.95)		(-0.56)
Constant	3.948***	-1.445***	3.953***	-0.824***
	(1615.61)	(-12.26)	(1782.61)	(-8.20)
Observations	12615	12351	17180	15946
Number of firmid	2199	2179	2695	2585
N	12615	12351	17180	15946
Wald Chi2	145.3***	3619.6***	362.4***	4040.4***

Note: z-statistics in parentheses *** p<0.01, ** p<0.05, * p<0.1

For high-tech firms (High-tech=1), Model 1 establishes a significant positive link between AI adoption and ESG performance (coefficient = 0.020, $p < 0.01$). Upon introducing control variables (such as Size, Lev, and TMTAge) in Model 2, the coefficient for AI drops to 0.010 ($p < 0.01$). This reduction implies that while AI remains a key driver, firm-specific characteristics explain a portion of the variation in ESG scores within the high-tech sector.

The results for non-high-tech firms (High-tech=0) offer a contrasting perspective. In Model 3, the baseline coefficient for AI is notably higher at 0.032 ($p < 0.01$). Even after adjusting for control variables in Model 4, the AI coefficient stands at 0.020 ($p < 0.01$). Crucially, this adjusted coefficient is double that of the high-tech sector, suggesting that AI integration yields a stronger marginal benefit for ESG performance in traditional industries.

Regarding the control variables, the trends remain consistent across both sectors. Firm Size and TMTAge are positively associated with ESG outcomes, underscoring the advantages of resource abundance and managerial experience. Conversely, Lev and Growth exert a negative influence, likely due to the resource constraints associated with debt and rapid expansion.

Overall, while AI promotes ESG performance universally, the impact is more potent in non-high-tech industries. A likely explanation is the ceiling effect: high-tech firms often operate with already elevated ESG standards driven by inherent innovation and strict regulatory scrutiny, leaving limited room for marginal improvement. In contrast, non-high-tech firms may leverage AI as a transformative tool to bridge sustainability gaps, resulting in a more dramatic positive shift.

4.4 Instrumental Regression

Table 7 presents the instrumental variable (IV) regression results, utilizing provincial-level AI development as an instrument for corporate AI adoption. The validity of this instrument rests on two pillars: relevance and exogeneity. We assume that while regional technological maturity directly influences a firm's access to AI infrastructure and talent, it does not directly dictate the firm's ESG performance other than through the channel of AI adoption. This approach aligns with literature suggesting that regional innovation ecosystems are critical drivers of firm-level technological capability.

Baseline OLS regressions (Models 1 and 2) establish a starting point, showing a positive link between AI and ESG. However, the IV models—estimated via TSLS, LIML, GMM, and IGMM—reveal a much stronger relationship. The coefficient for AI in these models is 0.358 ($p < 0.01$), which is substantially higher than the OLS estimates. This discrepancy suggests that standard OLS models likely suffered from downward bias due to endogeneity, effectively masking the true magnitude of AI's impact.

The IV estimation also alters the interpretation of control variables. For instance, Firm Size, which appeared significant in the OLS models, loses significance in the IV specifications. This shift implies that the OLS results may have conflated the effects of size with other omitted variables. Conversely, the consistency of the AI coefficient across various IV estimators (TSLS, LIML, etc.) provides robust evidence that the positive impact of AI on ESG is not a statistical artifact.

In conclusion, by correcting for endogeneity, this analysis demonstrates that AI development drives ESG performance more powerfully than traditional estimates suggest. These findings highlight the necessity of using rigorous identification strategies when evaluating the intersection of technology and corporate sustainability.

Table 7: Instrumental Variable Regression Analysis

VARIABLES	Model1	Model2	Model3	Model4	Model5	Model6
	OLS_no_AI	OLS_with_AI	TSLS	LIML	GMM	IGMM
AI		0.020***	0.358***	0.358***	0.358***	0.358***
		(23.37)	(17.95)	(17.95)	(17.95)	(17.95)
Size	1.133***	1.069***	0.094	0.094	0.094	0.094
	(73.12)	(69.22)	(1.24)	(1.24)	(1.24)	(1.24)
Lev	-0.019***	-0.018***	-0.011***	-0.011***	-0.011***	-0.011***
	(-13.99)	(-13.45)	(-3.30)	(-3.30)	(-3.30)	(-3.30)
Growth	-0.004***	-0.004***	0.001**	0.001**	0.001**	0.001**
	(-10.99)	(-10.53)	(2.19)	(2.19)	(2.19)	(2.19)
Board	-0.007	-0.008	-0.003	-0.003	-0.003	-0.003
	(-1.38)	(-1.61)	(-0.19)	(-0.19)	(-0.19)	(-0.19)
lnIndependent	0.022***	0.018**	-0.012	-0.012	-0.012	-0.012
	(3.14)	(2.56)	(-0.57)	(-0.57)	(-0.57)	(-0.57)
TMTAge	0.007***	0.007***	0.006***	0.006***	0.006***	0.006***
	(26.05)	(26.05)	(8.73)	(8.73)	(8.73)	(8.73)
lnmshare	0.002***	0.000	-0.025***	-0.025***	-0.025***	-0.025***
	(4.12)	(0.93)	(-12.24)	(-12.24)	(-12.24)	(-12.24)
Constant	0.030	0.240***	3.284***	3.284***	3.284***	3.284***
	(0.56)	(4.53)	(13.12)	(13.12)	(13.12)	(13.12)
Observations	28297	28297	21457	21457	21457	21457
R-squared	0.24	0.25				
N	28297	28297	21457	21457	21457	21457
r2_a	0.238	0.252	/	/	/	/
F	1260	1177	/	/	/	/

Note: Robust t-statistics in parentheses *** p<0.01, ** p<0.05, * p<0.1

5. Discussion

AI offers a promising pathway to strengthening ESG performance. It can sharpen resource allocation, deepen environmental analytics, and support strategic choices that better align with evolving social and governance norms. Firms that embrace AI are often better positioned to keep pace with regulatory updates and shifting stakeholder expectations, which in turn helps safeguard their access to capital, protect their market standing, and preserve reputational credibility. Adam, Alarifi^[31], and their co-authors (2021) make a related point, suggesting that AI functions as a strategic resource—one that helps organisations foresee and respond to ESG-related demands before they become pressing challenges.

That said, the ESG gains from AI are unlikely to be uniform across regions. In more advanced economies, where digital infrastructure is already dense and AI adoption is relatively mature, additional investments in the technology may yield only marginal improvements in ESG outcomes—a pattern consistent with the logic of diminishing returns. In less developed settings, however, the introduction of AI can be genuinely transformative. For firms operating with fewer technological assets, AI may offer a rare opportunity to leapfrog conventional stages of development, bringing about more pronounced gains in environmental and social performance. This resonates with the technology gap literature, and finds empirical support in Ginesti, et al. (2018)^[32], who document how AI-assisted medical tools have tangibly raised healthcare standards in rural parts of developing countries. What these observations point to is that the ESG impact of AI is deeply embedded in—and constrained by—the local economic and technological fabric.

A similar logic applies across industries. In high-tech sectors, where firms are already accustomed to deploying advanced tools, the additional ESG uplift from AI tends to be modest; their baseline performance is often elevated to begin with. Moreover, these companies frequently prioritise speed and product innovation over sustainability concerns, which may further dilute AI's ESG emphasis. By contrast, non-high-tech industries—many of which are only beginning to digitise—stand to benefit more noticeably from AI, especially in operational areas like energy monitoring, material efficiency, and waste management. These cross-industry variations remind us that AI's role in ESG is far from one-size-fits-all, and they underscore the importance of tailoring ESG strategies to the specific realities of each sector.

6. Conclusion and Future Research

6.1 Conclusion

Drawing on resource dependency theory, this paper explores the link between AI adoption and ESG performance in public firms, with a particular eye on how this relationship shifts across regions and sectors. Using regression analysis paired with instrumental variables to account for endogeneity, we find that AI's ESG effects are statistically significant but highly context-dependent. The data shows stronger improvements in economically lagging areas and non-high-tech industries. Our takeaway is straightforward: AI can be a force for good in ESG terms, but its effectiveness is not universal—it bends to the economic and industrial environment in which it is deployed.

6.2 Implications

For researchers, the work is far from over. We need a much sharper understanding of how AI can be fine-tuned to boost ESG results, especially in areas that haven't been scrutinized yet. Comparing different sectors and regions would be incredibly useful here; it would allow us to build a more detailed classification system that ties AI's potential directly to specific economic and industrial contexts. Theoretically, there is also a strong case for blending insights from innovation studies, strategic management, and CSR. Merging these fields could give us a much more complete picture of how to leverage AI for genuine corporate sustainability.

In the business world, the situation presents a mix of risk and reward. Companies in industries or regions where AI's impact on ESG is still unclear have a unique chance to take the lead. They can do this by piloting AI strategies that are explicitly designed to hit ESG targets. A practical first step? conducting internal AI audits. But these shouldn't just measure efficiency; they need to ask the hard

question: Are these tools actually aligned with our ethical and sustainability standards? Furthermore, companies should look beyond their own walls. Sharing successes and failures across industry lines ensures we aren't all reinventing the wheel when it comes to responsible AI.

Finally, for policymakers, the role is distinct but just as vital. They set the stage for how AI is built and used, effectively steering it toward outcomes that help society and the environment. This could involve directing funds toward AI research that tackles specific ESG hurdles or creating incentives for firms that use AI to tangibly improve their standing. At the same time, we need smart regulation—frameworks that demand transparency and accountability—to ensure that the rush to adopt AI in business doesn't leave ethical oversight behind.

6.3 Future Research

Future research on AI and ESG has several promising avenues. One key area is the longitudinal impact—tracking how ESG performance evolves alongside AI technology. Beyond compliance, studies should also examine how AI drives innovation and creates new sustainable business models. It is equally important to investigate the ethical dimensions, particularly AI's effect on labor markets and society. Furthermore, sector-specific analysis is needed to understand diverse industrial outcomes. Finally, granular, firm-level case studies are essential to evaluate the real-world effectiveness of strategic AI implementation.

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