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The Impact of Enterprise Digital Intelligence Transformation on Green Governance: Evidence from Chinese Heavy Pollution Enterprises

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Abstract

Enterprise digital intelligence transformation builds upon the digitalization of information and the enhancement of process-related services. It extends into the organization's core operations, aiming to establish an advanced business model that embodies a higher level of digital and intelligent integration. This study examines the impact of enterprise digital transformation on green technological innovation and operational performance; drawing on firm-level data from China's highly polluting industries between 2014 and 2024. Empirical results indicate that digital transformation significantly promotes green technological innovation, as evidenced by an increase in the number of green patents, thereby enhancing enterprises' capacity to fulfill social and environmental responsibilities. In contrast, its effect on operational and managerial performance is not statistically significant, although the positive coefficient suggests potential long-term gains. The relatively high initial investment required for digital infrastructure development and employee training, combined with substantial trial-and-error costs particularly for small and medium-sized enterprises appears to constrain short-term operational improvements. Furthermore, the findings suggest that while digital transformation acts as a catalyst for sustainability-oriented innovation, its economic benefits may follow a delayed realization pattern. This research extends the literature on digitalization and corporate green governance by focusing on high-emission industries, offering practical implications for policymakers, regulators, and managers seeking to balance environmental objectives with economic performance in the digital era.

Keywords: digital transformation, green technological innovation, enterprise performance, SMEs, sustainability.

Introduction

The rapid evolution of digital technologies has transformed the competitive landscape, providing enterprises with powerful tools to enhance innovation, optimize resource management, and strengthen sustainability performance. In contemporary business practice, Digital Intelligence Transformation (DIT) is the integration of advanced technologies such as artificial intelligence, big data analytics, blockchain, cloud computing, and the Internet of Things (IoT) is no longer viewed merely as a technical upgrade, but as a strategic imperative for maintaining long-term competitiveness and meeting stakeholder expectations. By enabling real-time data analysis, predictive decision-making, and process automation, these technologies support enterprises in reducing environmental footprints, improving operational efficiency, and fostering a culture of continuous innovation (Porter & Heppelmann, 2014).

Within the sustainability domain, Green Governance (GG) has gained prominence as a holistic approach to embedding environmental, social, and governance considerations into corporate strategy and operations. This aligns with stakeholder theory, which emphasizes that businesses are accountable not only to shareholders but also to broader communities and the environment (Suchman, 1995). Effective GG requires accurate environmental monitoring, transparent reporting, and proactive compliance with regulations capabilities that DIT is uniquely positioned to strengthen. For instance, IoT sensors can track emissions in real time, blockchain can ensure the integrity of ESG disclosures, and big data analytics can identify efficiency opportunities across the value chain.

Green technological innovation is particularly critical for heavy-pollution industries, where environmental regulations are stringent and societal pressure for corporate responsibility is high. Prior research (Zhang Li et al., 2025) indicates that digital transformation accelerates green innovation by facilitating knowledge sharing, shortening R&D cycles, and optimizing resource allocation. However, the relationship between DIT and broader enterprise performance remains complex. While digital initiatives may yield long-term sustainability gains, their operational and financial benefits often lag due to high upfront investment costs, lengthy infrastructure development, and the substantial effort required for employee training and process redesign. Small and medium-sized enterprises (SMEs), in particular, face higher risks from trial-and-error adoption and tighter financial constraints, which can slow the realization of returns (Urandelger & Otgonsuren, 2021).

Against this backdrop, the present study investigates the impact of DIT on GG within Chinese heavy-pollution enterprises, with particular attention to its role in fostering green technological innovation and influencing enterprise performance. By employing firm-level panel data and robust econometric methods, this research aims to contribute empirical evidence on how digitalization can serve as both a catalyst for sustainable innovation and a driver of enhanced governance practices, while also identifying structural and financial factors that may hinder the immediate operational benefits of transformation.

Theoretical Background and Hypotseses Development

Digital Intelligence Transformation

Digital Intelligence Transformation (DIT) refers to the integration and application of advanced digital technologies such as artificial intelligence, big data analytics, the Internet of Things, and automation within organizations to improve decision-making and operational processes. Unlike simple digital conversion, which involves converting analog information to digital form, DIT emphasizes leveraging intelligent technologies to enhance organizational efficiency, flexibility, and innovation capabilities (Bharadwaj et al., 2013). This transformation enables firms to gain timely insights and optimize their resource management, facilitating better adaptation to changing business environments. From the perspective of Dynamic Capabilities Theory (Teece, Pisano, & Shuen, 1997), firms that engage in digital intelligence transformation develop the ability to sense and seize new opportunities, as well as to reconfigure their operations to sustain competitive advantage. This theory underscores the importance of continuous learning and adaptability in turbulent markets. DIT empowers firms to apply these principles by using real-time data analytics and AI-driven decision-making tools, which is crucial for addressing complex challenges like environmental sustainability.

Green Governance

Green Governance (GG) represents a firm's adoption of policies, practices, and management structures aimed at promoting environmental sustainability. It aligns with the principles of Environmental, Social, and Governance (ESG) frameworks and reflects a commitment to reducing negative ecological impacts while enhancing transparency and accountability (Eccles, Ioannou, & Serafeim, 2014). Effective green governance involves not only complying with environmental regulations but also proactively managing resources to support long-term ecological balance. The theoretical underpinning of GG can be found in Stakeholder Theory (Freeman, 1984), which suggests that firms have responsibilities to a broad range of stakeholders beyond shareholders, including communities and the environment. By implementing green governance, firms respond to stakeholder expectations for environmental responsibility, thereby improving their legitimacy and social license to operate (Suchman, 1995).

Relationship between Digital Intelligence Transformation and Green Governance

Recent studies highlight that digital intelligence transformation can significantly facilitate green governance by enabling precise monitoring and management of environmental performance. Technologies such as IoT sensors, AI, and big data analytics allow firms to track emissions, resource usage, and waste in real time, leading to more effective environmental management systems (Porter & Heppelmann, 2014). According to the Resource-Based View (RBV) of the firm (Barney, 1991), digital intelligence capabilities constitute valuable and unique resources that help integrate environmental concerns into business strategies and operations. Consequently, firms that invest in digital intelligence transformation are better positioned to enhance their green governance, which can result in improved sustainability outcomes and competitive advantage.

Control Variables:

Firm Size: Larger firms usually possess greater financial and human resources, enabling more comprehensive implementation of green governance practices. Additionally, they often face increased scrutiny from stakeholders and regulators, incentivizing sustainability efforts (Campbell, 2007).

Firm Growth: Organizations experiencing growth are more likely to adopt sustainable practices to maintain legitimacy and support continued development (Bruton, Ahlstrom, & Li, 2015).

Leverage: High leverage ratios can restrict firms' ability to invest in green initiatives due to financial constraints (Jo & Harjoto, 2011).

Ownership Concentration: Firms with concentrated ownership structures may benefit from decisive governance and stronger commitment to sustainability policies, as large shareholders tend to influence strategic decisions more effectively (Shleifer & Vishny, 1997).

H1 Digital Intelligence Transformation has a positive effect on Green Governance.
(Firms with higher levels of digital intelligence transformation are more likely to implement effective green governance practices.)

H2 Firm size (Total Corporate Assets) positively influences Green Governance.
(Larger firms have more resources to implement green governance.)

H3 Firm growth positively influences Green Governance.
(Growing firms are more motivated to adopt sustainable and green policies.)

H4 Leverage (Total Liabilities / Total Assets) negatively affects Green Governance.
(Firms with higher debt ratios may have less financial flexibility to invest in green governance.)

H5 The shareholding ratio of the largest shareholder positively affects Green Governance.
(Higher ownership concentration encourages stronger commitment to sustainable governance.)

Methodology

Variable Definition

To assess the relationship between corporate green governance and digital transformation, this study defines and classifies variables into three major categories: dependent variables, independent variables, and control variables.

Table1. Variable definition

Variables	Factors	Explanation
Dependent	Green governance(ESG)	Hua Zheng ESG scores (0–100)
Independent	Digital	Based on text analysis and word frequency statistics, the digital-related words in the enterprise's annual report are processed and statistically analyzed
Control	Size	ln(Total Corporate Assets)
	Growth	(Current period operating income - Previous period operating income)/ Previous period operating income
	Lever	Total corporate liabilities/Total corporate assets
	top1	The shareholding ratio of the largest shareholder
	Board	ln(Number of Directors)
	Fcfe	Net profit + non-cash expenditure - capital expenditure - changes in net working capital + net borrowing

Empirical model

To study the impact of enterprise digital transformation on the ESG performance of enterprises, sets up the following benchmark regression model

$$ESG_{it} = \beta_0 + \beta_1 lndigital_{it} + \sum_j \beta_j Controls + \lambda i + \mu t + \varepsilon it$$

Among them, the explained variable is the enterprise's ESG performance (ESG), and the core explanatory variable is the enterprise's digital transformation (lndigital). Controls represent the aforementioned control variables, $\lambda_i$is the individual fixed effect, $\mu_t$is the time fixed effect, and $\varepsilon_{it}$is the random error term in the benchmark model. Parameter$\beta_1$reflects the impact effect of an enterprise's digital transformation on its ESG performance. To make the statistical inference results more robust, the regression model is estimated using a robust standard error.

Results

Descriptive statistics

Table 2 is a descriptive statistical table of the data in this paper. It can be found that the mean of the explained variable ESG is 72.60, the standard deviation is 5.95, and the 50th percentile is 72.73, indicating that the distribution is similar to a normal distribution. There are certain differences in ESG performance among enterprises, but overall, the differences are not significant. The core explanatory variable is the digital transformation of enterprises, with a mean of 2.94, a standard deviation of 7.44, a 50% quantile of 0, and a maximum value of 158. This variable has a relatively large standard deviation, and the maximum value differs significantly from the mean and minimum values, indicating that there are significant differences in the degree of digital transformation among enterprises, and some enterprises have not yet started digital transformation.

Table2. Descriptive Statistic

	ESG	lndigital	Size	Growth	lever	top1	board	FCFE
Count	10973	10973	10973	10973	10973	10973	10973	10973
Mean	72.60	2.94	22.73	34.65	40.83	34.00	2.13	669564800
Std	5.95	7.44	1.01	1145.93	27.75	14.87	0.20	5483653000
Min	36.62	0.00	19.72	-97.02	1.31	0.00	1.39	-136259000000
25%	69.54	0.00	22.01	-5.85	23.77	23.02	1.95	-111012300
50%	72.73	0.00	22.57	6.80	39.08	31.52	2.20	95092140
75%	76.01	3.00	23.31	20.97	55.14	43.15	2.20	518021600
Max	98.00	158.00	28.31	94409.96	1879.04	89.99	2.89	164190000000

Meanwhile, in order to explore the correlations among various variables, the study draws a heat map of correlation analysis as shown in Figure 1.The darker the color, the stronger the positive correlation between the two variables.

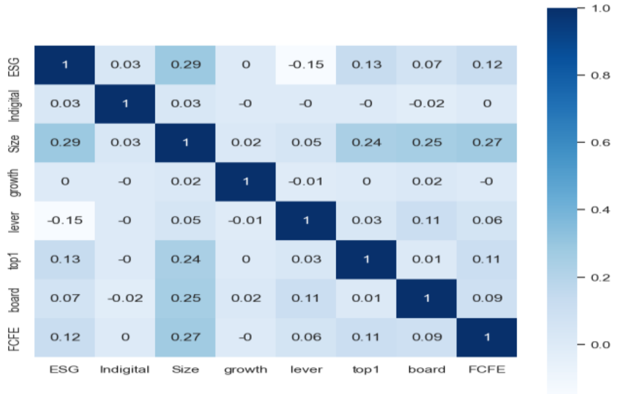

Figure1. Heatmap of correlation analysis

According to Figure 1, it can be found that there is a 0.03 correlation between digital transformation and ESG. The table indicates that digital transformation can positively affect the ESG of enterprises, although the impact is relatively small. However, the correlation analysis has no fixed time and individual differences. Therefore, in order to deeply explore the relationship between the two, it is necessary to use panel regression to further analyze the data.

Benchmark regression results

The study conducts a basic regression on the data. Column (1) of Table 3 shows the results of enterprise digital transformation with only the core explanatory variable, column (2) shows the results with some control variables added, and column (3) shows the results with all control variables added. According to Table 3, it can be found that only in the regression of the variable of enterprise digital transformation, the regression coefficient of enterprises is significantly positive. Meanwhile, after gradually adding control variables, the coefficient of enterprise digital transformation remains significant and is all positive. This indicates that enterprise digital transformation can positively affect the ESG performance of enterprises, that is to say, the digital transformation of enterprises can help enterprises better fulfill their social responsibilities. Realize the creation of non-economic value for enterprises.

Table3. Basic Regression Results

Variables	(1)	(2)	(3)
Indigital	0.023***	0.018***	0.017**
	(2.343)	(2.190)	(2.085)
Size		1.155***	1.106***
		(9.606)	(9.133)
Growth		0.000	0.000
		(-0.895)	(-0.895)
Lever		-0.021***	-0.021***
		(-9.519)	(-9.558)
Fcfe		0.000***	0.000***
		(4.424)	(4.355)
top1			0.022***
			(2.561)
Board			1.010***
			(2.114)
Constant	72.535	47.122	45.337
Individual fixed effect	YES	YES	YES
Time fixation effect	YES	YES	YES
Adjust R square	0.511	0.554	0.607
Observed value	10973	10973	10973

Robustness test

Firstly, the study adopts the method of replacing the core explanatory variables to test the robustness of the model. Since the dimension of enterprise digital transformation includes five aspects: artificial intelligence technology, blockchain technology, cloud computing technology, big data technology and digital technology application, this paper will replace the core explanatory variables with these four aspects respectively for regression. The regression results are shown in Table 4. It can be found that except for the artificial intelligence variable which is not significant, all other variables are significantly positive. Especially, the regression coefficient of blockchain technology is the largest compared to other variables, indicating that blockchain technology is of the greatest help to enterprises in improving their ESG level. The possible reasons for this analysis are: the essential characteristics of blockchain technology are in line with the core of ESG, and the immutable feature of blockchain technology fundamentally solves the most critical trust crisis problem in ESG practice. When enterprises store environmental data, social responsibility fulfillment and governance processes, all records have the characteristics of being verifiable, traceable and unalterable. This "digital authenticity" completely eliminates the "greenwashing" behavior in traditional ESG reports. In addition, the distributed governance feature of blockchain conforms to the ESG multi-party governance concept. Through mechanisms such as token voting, it enables small and medium-sized investors, environmental protection organizations and other stakeholders to directly participate in decision-making, effectively solving the agency problem in traditional corporate governance. This enables blockchain not only to optimize the technical process of ESG management but also to reconstruct the underlying logic of sustainable development for enterprises. Therefore, its depth of influence far exceeds that of other digital technologies, becoming the core factor driving ESG transformation.

Table4. Robustness Test for Replacing core Explanatory Variables

Variables	(1)	(2)	(3)	(4)	(5)
Artificial intelligence	0.0291				
	(0.662)				
Block chain		0.304***			
		(2.043)			
Cloud computing			0.1256***		
			(3.078)		
Big data				0.037* (1.921)	
Digital technology					0.012***
					(2.563)
Control	YES	YES	YES	YES	YES
Individual fixed effect	YES	YES	YES	YES	YES
Time fixation effect	YES	YES	YES	YES	YES
Adjust R	0.610	0.611	0.624	0.609	0.609

square					
Observed value	10973	10973	10973	10973	10973

Endogeneity test

The data in the table presents the specific results of the endogeneity test, including information such as different lag terms, coefficients under instrumental variable regression, statistics, and model fitting conditions.

Table5. Endogeneity test results

Variables	（1） ESG	（2） ESG	（3） ESG	（4） Indigital	（5） ESG
L. Indigital	0.045*** (2.009)				
L2. Indigital		0.078** (1.761)			
L3. Indigital			0.081** (1.005)		
Instrumental variable				0.000*** (76.989)	
lndigita1					0.000*** (3.558）
Hausman Statistics					0.000***（27.1）
Control	YES	YES	YES	YES	YES
Individual fixed effect	YES	YES	YES	YES	YES
Time fixation effect	YES	YES	YES	YES	YES
Adjust R square	0.652	0.642	0.621	0.387	

The study verifies the robustness of the conclusion through two approaches to address the potential endogenous causal relationship between enterprise digital transformation and ESG performance. Firstly, considering that the impact of digital transformation on ESG has a time lag, the core explanatory variable is introduced with a lag of 1-3 periods for regression (columns 1-3 in the table). The results show that the coefficients of each lag term are all positive at the 10% significance level, and the adjusted R^2 is between 0.621 and 0.652, indicating that the core conclusion still holds under the lag effect. Second, the Lewbel (1997) method was adopted to construct instrumental variables, with the cube of the difference between the enterprise's digital transformation and the industry average being used as the instrumental variable. In the first stage of regression in Column 4, the coefficient of the instrumental variable is significantly positive at the 1% level, meeting the correlation condition. The results of the second stage in Column 5 show that all Hausman statistics have passed the test, eliminating the problems of insufficient identification and weak instrumental variables. Moreover, the coefficients of the core variables remain significantly positive, and the verification results are also robust.

Mechanism Verification

In the previous analysis, the study confirmed through benchmark model regression, robustness tests and endogeneity tests that enterprise digital transformation has a significant positive effect on corporate social responsibility (ESG). However, the above analysis only examined the relationship between enterprise digital transformation and social responsibility, and the underlying mechanism of action remains unknown. Therefore, this section draws on Xiao, H., Yang, Z., & Ling, H. (2022) methodological framework and uses mediating variables to conduct a mechanism test on the transmission path between digital transformation and ESG performance.

The study refers to the practices of Song Deyong et al. (2022). To analyze the green technological innovation effect of enterprise digital transformation, this paper selects the number of green patents to measure the green technological innovation effect. The number of green patents includes: The number of green invention patents and the number of green utility model patents, and taking the logarithm of them as mediating variables for analysis (Ingp); In addition, in order to explore the mechanism of the impact of enterprise digital transformation on enterprise operation and management, this paper uses the enterprise's profit margin on sales (Ros) as a mediating variable for analysis. The analysis results are shown in Table 6. It can be found that the digital transformation of enterprises has a significant positive impact on green technological innovation, indicating that digital transformation has driven an increase in the number of green patents of enterprises, thereby enhancing their green innovation capabilities and ultimately promoting enterprises to better fulfill their social responsibilities. It is worth noting that the digital transformation of enterprises does not significantly affect the operation and management of enterprises, but a positive coefficient indicates that there is a positive impact. The possible reason for this is that the initial investment cost for digital transformation is relatively high, and it is often difficult to translate into operational and production achievements in the short term. Especially during the period of technical infrastructure construction and employee skills training, enterprises need to bear a significant financial burden, so their sales profit margin cannot be significantly improved in the short term. At the same time, small and medium-sized enterprises have a large space for management optimization during the process of digital transformation, and the cost of trial and error is relatively high, which to some extent hinders the digital transformation returns of small and medium-sized enterprises. This is similar to the research conclusions of Zhang Li et al. (2025).

Table6. Mechanism Analysis

	Ingp	Ros
Indigital	0.0033^{***}	0.0082
	(2.384)	(0.259)
Control	YES	YES
Individual fixed effect	YES	YES
Time fixation effect	YES	YES
Adjust R square	0.211	0.139
Observed value	4984	10973

Discussion

The empirical findings of this study provide robust evidence that enterprise Digital Intelligence Transformation (DIT) has a significant and positive effect on Green Governance (GG) among Chinese heavy-pollution enterprises. This is consistent with prior research suggesting that digital technologies enable firms to integrate sustainability into their strategic and operational frameworks (Porter & Heppelmann, 2014; Bharadwaj et al., 2013). Across all regression specifications, the coefficient for DIT remained positive and statistically significant, indicating that greater adoption of intelligent digital technologies strengthens firms' ESG performance. This aligns with the Resource-Based View (Barney, 1991), which posits that unique technological capabilities can be leveraged as strategic assets for sustainable competitive advantage. The results also highlight the heterogeneous effects of specific digital technologies. Blockchain technology emerged as the most influential component of DIT for improving ESG outcomes, surpassing artificial intelligence, cloud computing, big data, and other digital applications. This finding resonates with the argument that blockchain's immutable and transparent nature addresses trust deficits in ESG disclosures and mitigates "greenwashing" (Zhang et al., 2025). By ensuring verifiable and tamper-proof environmental records, blockchain aligns closely with multi-stakeholder governance principles and supports more credible sustainability reporting. Control variables further reinforce theoretical expectations. Larger firms exhibited stronger green governance, reflecting their greater access to resources and higher public scrutiny (Campbell, 2007). Conversely, leverage negatively affected ESG performance, indicating that financial constraints may hinder sustainability investments (Jo & Harjoto, 2011). Ownership concentration and board size also had positive effects, suggesting that effective governance structures facilitate ESG-oriented decision-making (Shleifer & Vishny, 1997). Mechanism analysis revealed that DIT enhances GG primarily through green technological innovation, as evidenced by the increased number of green patents. This supports prior studies asserting that digital transformation can accelerate innovation in environmentally friendly technologies (Hu, 2022). However, the absence of a significant short-term effect on profitability (ROS) suggests that while DIT may generate long-term sustainability benefits, its financial returns may be delayed due to high upfront investment costs, infrastructure development, and workforce upskilling requirements. Overall, these findings contribute to the growing body of literature linking digital transformation with corporate sustainability, particularly in high-impact sectors. They emphasize the role of advanced digital capabilities not only in operational efficiency but also in fostering a culture of transparency, stakeholder engagement, and environmental responsibility.

Conclusion

This study empirically demonstrates that Digital Intelligence Transformation is a critical driver of Green Governance in Chinese heavy-pollution enterprises. By employing panel regression models, robustness checks, endogeneity tests, and mechanism analysis, the research establishes that firms engaging in higher levels of DIT achieve significantly better ESG performance. Among various digital technologies, blockchain stands out as the most potent enabler, reflecting its capacity to enhance data integrity, stakeholder trust, and participatory governance. The analysis further reveals that DIT promotes GG through increased green technological innovation, as measured by the number of green patents, although its short-term impact on profitability is limited. This suggests that policy makers and corporate leaders should view DIT as a strategic, long-term investment in sustainable development rather than a source of immediate financial gain. From a managerial perspective, the findings underscore the importance of prioritizing advanced digital technologies particularly blockchain in sustainability strategies. For policy makers, the results highlight the need to create supportive environments that encourage digital adoption, especially in resource-intensive and environmentally sensitive industries. Future research could extend this work by exploring cross-industry comparisons, examining the role of organizational culture in mediating the DIT-GG relationship, and assessing the long-term financial payoffs of digital-driven sustainability initiatives.

Limitation

While this study offers important insights into the relationship between Digital Intelligence Transformation (DIT) and Green Governance (GG) in Chinese heavy-pollution enterprises, several limitations should be acknowledged. First, the analysis is based on secondary firm-level data, which, despite its comprehensiveness, may not fully capture qualitative dimensions of digital adoption such as organizational culture, managerial commitment, or employee competencies. These intangible factors can significantly influence both the implementation and the effectiveness of DIT, yet they remain outside the scope of this study.

Second, the measurement of DIT relies on text-mining of corporate annual reports, which, although methodologically robust, may be subject to reporting bias. Firms with stronger ESG reputations may be more inclined to highlight their digital initiatives, potentially overstating the extent of their transformation efforts.

Third, the study focuses exclusively on heavy-pollution industries in China, which limits the generalizability of the findings to other sectors or national contexts. Regulatory environments, market structures, and stakeholder expectations vary widely across industries and countries, and these differences could moderate the observed relationships.

Fourth, the operational and managerial impacts of DIT are examined over a relatively short time frame. Given the long-term nature of both digital transformation and sustainability outcomes, future research should adopt a longer observation period to capture delayed effects, particularly on profitability and operational efficiency.

Finally, the empirical model, while incorporating several relevant control variables, may still be affected by omitted variable bias. External factors such as changes in environmental regulations, government incentives for digital adoption, or industry-specific technological trends were not directly included but could influence both DIT and GG outcomes.

These limitations present opportunities for future studies to adopt mixed-method approaches, expand the scope to cross-industry and cross-country comparisons, and incorporate longitudinal data to better understand the long-term and context-specific effects of DIT on sustainability performance.

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