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The promoting effect of enterprise digital transformation on green innovation： A perspective of corporate governance

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Abstract: As digital technology advances, the digital economy has profoundly reshaped industrial ecosystems and transformed the broader economic landscape. The digital transformation of enterprises represents a microcosm of this shift and is a critical area of study, particularly in terms of its potential to drive green innovation. This paper uses data from Chinese A-share listed companies from 2012 to 2022 to examine the impact and underlying mechanisms of enterprise digital transformation on green innovation. Additionally, it investigates the effects of digital transformation on both substantive and strategic green innovations. Using textual analysis, the study constructs a measure of digital transformation and conducts an empirical analysis to assess its influence on green innovation. The findings are as follows: First, enterprise digital transformation has a significant positive impact on green innovation, with a stronger effect observed on substantive innovation compared to strategic innovation. This conclusion remains robust after performing several robustness checks. Second, through a heterogeneity analysis, the study reveals regional and industrial differences. Specifically, the effect of digital transformation on green innovation is more pronounced in the eastern and western regions compared to the central region, and it remains significant regardless of whether the enterprise operates in a high-pollution industry. Third, the study confirms that corporate governance mechanisms play a key role. Empirical results show that digital transformation promotes green innovation by enhancing corporate governance practices. These findings contribute to the understanding of how enterprise digital transformation can promote green innovation, offering empirical evidence for better facilitating a green and low-carbon transition in enterprises.

Keywords: Digital Transformation; Green Innovation; substantive green innovation; strategic green innovation; Corporate Governance

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1 Introduction

The digital economy and green development have emerged as two critical trends driving global economic and social transformation. Since the release of China's "Twelfth Five-Year Plan for the Development of Strategic Emerging Industries" in 2012, the focus has increasingly shifted toward emerging technologies, such as the Internet of Things (IoT) and cloud computing, underscoring the integration of informatization and industrialization. In March 2017, China formally incorporated the digital economy into its government report, highlighting its growing significance. The digital economy, a new economic paradigm driven by advances in information technology, has since profoundly influenced economic and social activities. In April 2020, the National Development and Reform Commission (NDRC) outlined key infrastructure priorities, including digital transformation, intelligent upgrading, and integrated innovation, specifying seven major development directions. By 2022, China's digital economy surpassed 50 trillion yuan, accounting for 41.5% of the country's GDP. The nominal value of the digital economy grew by 10.3% year-on-year in 2022, outpacing overall GDP growth. With its characteristics of high innovation, strong penetration, and broad coverage, the digital economy facilitates the flow of factors of production and the integration of market themes, overcoming temporal and spatial limitations while extending industrial chains.

As a new engine of economic growth, the digital economy accelerates the upgrading of traditional industries. At the micro level, digital transformation empowers enterprises by reshaping their production systems, management structures, and core processes through digital technologies, thus driving disruptive innovation (Siebel, 2019).

In parallel, green and low-carbon development has become a global imperative aligned with the interests of all nations. This momentum was reinforced when China announced its "dual-carbon" goals in December 2020, pledging to peak carbon emissions by 2030 and achieve carbon neutrality by 2060. These goals emphasize the critical role of enterprises as innovation leaders in supporting national green and low-carbon technological initiatives, thereby fostering scientific and technological revolutions. Under these objectives, the synergy between digitalization and green development is evident, as digital transformation enhances operational efficiency, optimizes resource allocation, and promotes green innovation. By integrating the digital economy with traditional industries, enterprise digital transformation plays a pivotal role in enabling green innovation, improving internal processes, decision-making mechanisms, and resource allocation efficiency, and reinforcing environmental measures such as pollution prevention and energy conservation.

The digital economy represents the next stage in economic evolution, following the agricultural and industrial economies. Enterprises, as microcosms of broader society, are key drivers of green innovation through digital transformation, contributing significantly to the economy's broader green and low-carbon development. Enterprise digital transformation not only fosters innovation (Jin et al., 2022) but also improves corporate governance (Qi et al., 2020), increases overall factor productivity (Guo et al., 2023), enhances green innovation efficiency in manufacturing (Liu et al., 2023), and promotes high-quality development within enterprises (Zhao et al., 2021).

This paper investigates how enterprise digital transformation influences green innovation, with a focus on regional and industry-specific heterogeneities and the mediating role of corporate governance. The study contributes to the body of digital economy theory by providing insights that can support the promotion of enterprise digital transformation, enhance corporate governance, and drive green innovation

2 Theoretical Background and Hypotheses

2.1 Impact of Digital Transformation on Green Innovation

Fussler and James (1996) were the first to introduce the concept of green innovation, defining it as a new product or technology that not only generates economic benefits for businesses but also reduces environmental impact. Green innovation refers to technological innovations in production methods, materials, and products that reduce energy consumption and improve the ecological environment (Qi et al., 2018). Driessen et al. (2013) argue that green innovation should not aim to merely reduce environmental burdens, but rather to achieve significant environmental benefits.As research on green innovation deepens, the connotation of green innovation is continually enriched. This paper argues that green innovation reduces negative environmental impacts by developing new products and technologies, thereby generating environmental benefits.

According to the resource-based view (RBV) theory, an enterprise's unique resources and capabilities are essential for sustaining long-term competitive advantages. This theory suggests that to address environmental challenges and achieve sustainable growth, enterprises must develop technological advantages (Song et al., 2022). In this context, there is a synergistic relationship between enterprise digital transformation and green innovation. This study posits that digital technologies play a pivotal role in driving innovation, particularly green innovation. By leveraging digital technology, companies can transform traditional business models, improve resource utilization, and enhance environmental performance. Additionally, digital transformation encourages greater investment in research and development (R&D) and the creation of patents (Liu et al., 2023; Jin et al., 2022).

First, digital transformation facilitates information sharing and knowledge integration, thereby strengthening an enterprise's green innovation capabilities. It fosters collaborative innovation ecosystems through digital platforms that streamline data aggregation (Wang et al., 2022), human resource management, and other essential inputs. This process enhances organizational flexibility and enables independent innovation. Technologies such as big data, cloud computing, and artificial intelligence (AI) allow enterprises to capture critical information regarding economic trends, market demands, technological advancements, and green development opportunities in real time. By analyzing large datasets related to innovation behaviors, companies can identify optimal paths and methodologies for innovation, thereby optimizing the innovation process and improving both the efficiency and effectiveness of green innovation efforts.

Furthermore, digital transformation enables more intelligent resource management. Through the use of the Internet of Things (IoT), sensors, and big data analytics, enterprises can monitor and optimize resource utilization in real-time, continuously refining their resource allocation and business processes. This digital foundation reinforces the quality and efficiency of green innovation initiatives.

In practical corporate settings, the impact of digital transformation on green innovation is evident. For example, in the power industry, which faces the challenge of meeting "dual carbon" objectives, thermal power plants are required to rapidly upgrade technologies to accommodate new energy sources and manage increasingly complex data flows. Leveraging 5G technology for comprehensive data monitoring and intelligent process management has significantly enhanced operational efficiency in this sector.

Based on this discussion, this paper proposes the following central hypothesis:

H1: Enterprise digital transformation can promote green innovation.

2.2 Impact of Digital Transformation on Substantive and Strategic Green Innovation

Based on a enterprise's strategic orientation and external environmental influences, different approaches to green innovation emerge. Li and Zheng (2016) argue that substantial innovation within enterprises represents a high-level form of innovation capable of driving technological advancement and enhancing a company's competitiveness. In contrast, strategic innovation is typically considered a lower-level form of innovation, often pursued to comply with regulatory policies and having a limited substantive impact on the company's long-term development.

Enterprises adopt different green innovation approaches depending on their operational conditions, strategic positioning, and external regulatory pressures. Typically, enterprises choose strategic green innovation to meet regulatory requirements, as it demands less investment and can achieve short-to-medium-term results. However, enterprises that pursue substantial green innovation face greater uncertainties and longer investment horizons. Nevertheless, such firms can gain lasting competitive advantages through high-tech green innovations. Therefore, this study categorizes green innovation into two types: substantial innovation and strategic innovation. Drawing on existing research (Zhang et al., 2023; Jia and Zhang, 2023), this study measures strategic green innovation through green utility model patents and substantial green innovation through green invention patents.

In the digital age, enterprises with a higher degree of digitization tend to be more proactive in innovation, favoring investments in high-tech, substantial green innovations, which lead to the generation of more patents and the creation of technological barriers (Zhang et al.,2024). Additionally, highly digitized companies tend to increase their expenditures on technology upgrades and talent development, further strengthening their capacity for green innovation. Compared to strategic green innovation, digital transformation plays a more significant role in fostering substantial green innovation.

Based on this understanding, the following hypothesis is proposed:

H2: The promoting effect of enterprise digital transformation on substantial green innovation is greater than its effect on strategic green innovation.

This hypothesis suggests that digital transformation, by enhancing operational efficiencies, facilitating data-driven decision-making, and fostering innovation ecosystems, empowers enterprises to undertake more impactful green innovations that align with long-term sustainability goals and provide competitive advantages.

2.3 The Mechanism by which Digital Transformation Influences the Green Innovation

The digital transformation of enterprises affects green innovation by improving corporate governance. A key challenge in modern corporate governance is the agency problem, which arises from the separation of ownership and control. According to Jin et al. (2022), digital transformation can mitigate agency issues, thereby fostering green innovation. By enhancing information transparency and reducing agency costs, digital transformation optimizes the internal organizational structures of enterprises (Hu and Liu, 2018; Qi and Xiao, 2020). Information technology enables shareholders to gain a clearer understanding of whether business decisions align with their interests, facilitating more effective oversight of management at lower costs. This, in turn, reduces information asymmetry between large and small shareholders and strengthens governance practices.

Given the high levels of uncertainty and risk inherent in innovation activities, which often fail to deliver immediate economic returns, self-interested managers may prioritize short-term gains and risk aversion. However, from a long-term perspective, digital transformation can help establish strong technological barriers, enhance corporate reputation, and improve capital market performance (Aragón-Correa et al., 2003; Jin et al., 2024). In the context of green innovation, enterprises face lengthy R&D cycles, high entry barriers, and increased specialization, which, combined with greater information opacity, make it difficult for shareholders to exercise effective oversight. Shen and Tan (2022) suggest that self-serving managers are likely to forgo innovation strategies in favor of pursuing short-term benefits. Nevertheless, digital transformation significantly enhances corporate governance by reducing information asymmetry and irrational decision-making (Qi et al., 2020). As businesses face increasingly complex challenges, digital technologies provide critical support in management, operations, financing strategies, and other related areas.

Based on this, the following hypothesis is proposed:

H3: Digital transformation can promote green innovation by improving corporate governance.

3 Research method

3.1 Data Source

This study utilized data from A-share listed companies from 2012 to 2022, with the following sample selection criteria: (1) Exclusion of companies with trading statuses of ST, ST*, and PT in the current year, and exclusion of the financial industry; (2) Exclusion of companies listed in 2022; (3) Exclusion of samples containing missing values for variables included in the regression. To mitigate the impact of outliers on the analysis results, all continuous variables were subjected to 1% winsorization. Text analysis data in this study were based on corporate annual reports from the Cninfo website; financial indicators of listed companies were sourced from the CSMAR database, and green patent data of listed companies were sourced from the CNRDS database.

3.2 Variable Definitions

3.2.1 Measurement of Dependent Variables

In this paper, In this study, the number of green patents independently filed by firms is used as the measure of green innovation. In China, green patents are classified into two types: green invention patents and utility model patents. To obtain a comprehensive measure of green innovation (denoted as Ginnov), this study aggregates these two types of patents. Compared to utility model patents, green invention patents are more challenging to acquire, as they emphasize "prominent substantive features" and "significant progress" in innovation, reflecting higher technological value. Therefore, green invention patents are considered substantial innovations in green technology, represented by the variable Ginv. On the other hand, utility model patents provide protection primarily for the product itself and are easier to obtain. The number of green utility model patent applications is represented by Gum. To normalize the data, the natural logarithm of the patent count plus one is applied to both variables.

3.2.2 Measurement of Independent Variable

Existing research primarily utilizes scale methods, index methods, and text analysis to measure enterprise digital transformation. This study adopts the text analysis approach to construct indicators for measuring digital transformation. Text analysis is typically performed by counting the frequency of specific phrases within selected texts. By doing so, qualitative textual data are compressed into phrase frequencies, allowing for the transformation of qualitative data into quantitative counts for empirical research.

To provide a comprehensive reflection of the adoption of various digital technologies by enterprises, this study constructs a set of digital transformation indicators for listed companies. The textual data from the annual reports of A-share listed firms are utilized, leveraging Python's web scraping and text recognition capabilities to extract the frequency of terms related to digital transformation. The frequency data is then aggregated across multiple dimensions to measure the level of digital transformation in enterprises.

The construction of the digital transformation indicators follows these steps:

First, based on policy documents such as the "14th Five-Year Plan for Digital Economy Development" and the "Action Plan for Promoting Cloud Computing and Data Utilization to Foster New Economic Development," as well as the methodologies of Wu et al. (2021), Zhao et al. (2021), and Jin et al. (2024), the digital transformation indicators are classified into three main categories and eight subcategories:

1.Digital foundational technologies, consisting of five specific categories: Big Data, Artificial Intelligence, Cloud Computing, Blockchain, and the Internet of Things.

2. Applications of digital technologies, which include Internet Business Applications and Smart Applications.

3. Digital support technologies, represented by Information Systems.

Second, the "seed word + Word2Vec similar words" approach is applied. Word2Vec refers to a neural network-based word embedding method that represents vocabulary as multidimensional vectors based on contextual semantic information. By calculating the similarity of these vectors, the semantic similarity between words is measured. This study focuses specifically on the Management Discussion and Analysis (MD&A) sections of the annual reports to expand the set of digital keywords. Python is employed to represent the vocabulary as multidimensional vectors, and the similarity between words is calculated to create a comprehensive set of digital terms.

Lastly, the total count of vocabulary containing digitalization related keywords is compiled. By adding one to the total word frequency related to digital transformation and then applying the natural logarithm, the digital transformation indicator digit is obtained. The process of indicator construction is as follows:

Table 1 Textual Feature Map of Digital Transformation

Category	Sub-category	Keywords
foundational Technology	Big Data	Big data, virtual reality, augmented reality, data management, data mining, data science, data centers, data platforms, data storage, visualization, data elements, data cleansing, text mining, data control, data technology, mixed reality, data systems, intelligent data analysis, multidimensional analysis, algorithms, public data, information retrieval
	Artificial Intelligence	Artificial intelligence, machine vision, deep learning, voice recognition, human-computer interaction, semantic search, business intelligence, face recognition, interactive technology, machine learning,

		biometrics, neural networks, image recognition, pattern recognition, image encoding, intelligent algorithms, metalanguage, expert systems, reinforcement learning, robotics
	Cloud Computing	Cloud computing, hybrid cloud, cloud ecosystem, virtualization, grid computing, cloud storage, multicloud management, edge computing, automated computing, private cloud, converged architecture, public cloud, cross-cloud, cloud operations, heterogeneous computing, cloud disaster recovery, computing resources, parallel computing, EB level, container technology, software-defined networking, software-defined storage, PAAS, IAAS, SAAS, hybrid cloud, cloud technology, cloud architecture, cloud strategy, virtual machines, cloud operating systems
	Blockchain	Blockchain, smart contracts, digital currency, distributed computing, consensus mechanisms, cross-chain, distributed systems, electronic money, parallel processing, public chains, private chains, tokens, encryption algorithms, off-chain, data warehouses, side chains, Ethereum
	Internet of Things	Internet of Things, RFID, sensors, wireless sensing, wireless communication, infrared scanning, IoT protocols, infrared sensing, wireless sensing, IoT architecture, IoT services, remote monitoring, IoT platforms, electronic tags, sensor networks, PML, readers, barcodes, WSN, HART, WSN, location tracking, online monitoring, 5G, 4G
Technology Application	Internet Business Models	Internet business models, online to offline, Internet models, Internet finance, Internet platforms, Internet ecosystems, Internet marketing, Internet applications, Internet business, offline to online, Internet strategies, e-commerce, Internet+, digital marketing, Internet services, cross-border e-commerce, O2O, B2B, C2C, B2C, C2B, online advertising, live commerce, mobile social, short videos, e-commerce platforms, mobile app stores, public accounts
	Intelligent Applications	Smart governance, digital twins, intelligent transportation, smart energy, smart parks, intelligent customer service, smart factories, smart agriculture, mobile connectivity, future factories, intelligent supply chains, intelligent manufacturing, sharing economy, NFC payments, mobile payments, collaborative office, fintech, digital finance, digital marketing, smart environmental protection, industrial internet, smart logistics, smart water management, smart tourism, smart education, city brain, intelligent warehousing, smart wearables, integrated marketing, digital intelligence, autonomous driving, Fintech, cloud brain, cloud warehouse, unmanned retail, industrial robots, electronic payments
Technical Support	Information Systems	Information systems, information integration, information networks, information software, information terminals, information sharing, information management, information centers, information communication, data terminals

3.2.3 Measurement of Control Variables

Drawing on methodologies from existing paper (Zhao et al., 2021) and following the approaches of Xu and Cui (2020) , the following control variables are selected as shown in Table 2.

Table 2: Variable Descriptions

Variable	Symbol	Variable Name	Variable Explanation
Dependent Variables	Ginnov	Total Quantity of Green Innovation	ln(total green patent applications + 1)
	Ginvia	Substantive Innovation	ln(green invention patent applications + 1)
	Gumia	Strategic Innovation	ln(green utility model patent applications + 1)
Independent Variable	Digit	Digital Transformation	ln(frequency of digitalization keywords + 1)
Control Variables	Size	Enterprise Size	ln(total assets of listed companies)
	Age	Enterprise Age	The observation year minus the year of establishment of enterprise
	Lev	Leverage Ratio	Total liabilities/Total assets
	Shconcern	Shares Concentration	Proportion of shareholding by the to ten shareholders
	ROA	Financial Performance	Return on total assets
	ReAsset	Risk Resistance	Retained earnings to asset ratio
	TQ	Enterprise Growth	Tobin-Q
	Subsidy	Government Subsidy	ln(annual subsidy received + 1)
	Boardsize	Board Size	Measured by the number of board members

3.3 Empirical Model

$$Ginnovation_{i,t} = \alpha_1 Digit_{i,t} + \alpha_2 Controls_{i,t} + \sum Time + \varepsilon_{i,t}$$

Ginnovation includes the total amount of green innovation (Ginnov), substantive innovation (Ginvia), strategic innovation (Gumia). These refer to the total number of green patent applications, green invention patent applications, and green utility model patent applications, subscripts represent the level of green innovation of enterprise i in year t; Digit represents the degree of digital transformation of enterprise; Controls represent control variables; To mitigate potential endogeneity issues, fixed effects for years are controlled.

4 Empirical Analysis Results

4.1 Descriptive Statistical Analysis

Table 3 displays the descriptive statistics of the main variables. The mean of Green Innovation (Ginnov) is 0.784, with a standard deviation of 1.096; Substantial Innovation (Ginvia) has a mean of 0.509 and a standard deviation of 0.884; Strategic Innovation (Gumia) has a mean of 0.524 with a standard deviation of 0.864. This indicates significant differences among different A-share listed companies in terms of green innovation, substantial innovation, and strategic innovation. The mean of the independent variable(Digit) is 2.322, with a standard deviation of 1.366.

Table 3：Descriptive Statistical Analysis

Variable	Max	Min	Mean	p50	SD	N
Ginvia	3.951	0	0.509	0	0.884	32286
Gumia	3.584	0	0.524	0	0.864	32286
Ginnov	4.394	0	0.784	0	1.096	32286
Digit	5.617	0	2.322	2.303	1.366	32286
Size	26.24	19.93	22.20	22.01	1.290	32286
Age	33	6	18.64	19	5.784	32286
ROA	0.198	-0.262	0.0370	0.0380	0.0640	32286
Lev	0.894	0.0540	0.413	0.402	0.204	32286
Shconcern	0.906	0.242	0.592	0.602	0.151	32286
ReAsset	0.580	-0.809	0.174	0.186	0.197	32286
TQ	8.585	0.842	2.038	1.616	1.309	32286
Subsidy	10.51	0	4.673	5.130	2.873	32286
Boardsize	14	5	8.439	9	1.606	32286

Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

4.2 Basic Regression Results

Table 4 presents the baseline regression results illustrating the relationship between digital transformation and green innovation. In Column (1), the core explanatory variable—digital transformation—shows a positive correlation with green innovation, with a coefficient of 0.061, significant at the 1% level. This suggests that digital transformation significantly enhances enterprise green innovation, providing strong support for Hypothesis H1 of this study.

Columns (2) and (3) display the regression results for digital transformation's impact on substantive green innovation and strategic green innovation, respectively. The regression coefficients are 0.047 and 0.042, both significant at the 1% level. These results indicate that digital transformation promotes both substantive and strategic green innovation.

To further compare the differences between these two coefficients, this study employs the Seemingly Unrelated Regression (SUR) model to test the coefficient differences between groups (suest). The test results show a chi-squared value of 599.34, with a p-value of 0.0000, significant at the 1% level. This indicates a statistically significant difference between the two coefficients. Thus, while digital transformation promotes both substantive and strategic green innovation, its effect is more pronounced on substantive innovation. These findings lend support to Hypothesis H2.

Table 4 Basic Regression Results

	(1)	(2)	(3)
	Ginnov	Ginvia	Gumia
Digit	0.061***	0.047***	0.042***
	(0.006)	(0.005)	(0.005)
Controls	Yes	Yes	Yes
N	32286	32286	32286
r2	0.158	0.114	0.116
Time	Yes	Yes	Yes

Standard errors in parentheses * p < 0.1, ** p < 0.05, *** p < 0.01

4.3 Robustness test

4.3.1 Mitigate the Impact of the COVID-19 Pandemic

From 2020 to 2022, the COVID-19 pandemic had a substantial impact on China's economic development, significantly disrupting the production and operations of enterprises. To assess this impact, the sample data in this study are divided into two periods: the pandemic period (2020-2022) and the pre-pandemic period (2012-2019). The regression results, considering the effects of the pandemic, are presented in Table 5.

Column (1) shows the results for the pandemic period, where the impact on green innovation is significant at the 10% level. However, Columns (2) and (3) indicate that the effects on substantive and strategic green innovation are statistically insignificant during this period. In contrast, Columns (4) to (6) present the regression results for the pre-pandemic period, where the outcomes are significant at the 1% level. These results suggest that, after accounting for the potential influence of the COVID-19 pandemic, the regression findings remain robust and consistent.

Table 5 The Regression Results of Mitigate the Impact of Covid-19 Pandemic

	2020-2022			2012-2019		
	(1)	(2)	(3)	(4)	(5)	(6)
	Ginnov	Ginvia	Gumia	Ginnov	Ginvia	Gumia
Digit	0.027*		0.023	0.044***	0.036***	0.027***
	(0.017)	(0.014)	(0.014)	(0.007)	(0.006)	(0.006)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
r2	0.061	0.026	0.073	0.153	0.117	0.108
Time	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses * p < 0.1, ** p < 0.05, *** p < 0.01

4.3.2 Lagged Regression Analysis

To further mitigate the endogeneity problem, this paper explores the lagged regression methods respectively to conduct the robustness. The number of green patents independently applied for by listed companies in the next period and two periods later is used as the dependent variable for re-examination, as shown in Table 6. The empirical results indicate that the regression coefficients of enterprise digital transformation on green technology innovation, substantive innovation, and strategic innovation are all positive and significant at the 1% level. The higher the level of enterprise digital transformation, the higher the level of green innovation in the next one or two periods, which further confirms the conclusions drawn earlier. The regression results are robust.

Table 6: Analysis of Lagged Regression Results

	Lagged one period			Lagged two period		
	(1)	(2)	(3)	(4)	(5)	(6)
	Ginnov	Ginvia	Gumia	Ginnov	Ginvia	Gumia
L.Digit	0.065***	0.058***	0.035***			
	(0.007)	(0.006)	(0.006)			

L2.Digit				0.044***	0.040***	0.020***
				(0.007)	(0.006)	(0.006)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
r2	0.147	0.104	0.110	0.123	0.087	0.093
Time	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

4.3.3 Propensity Score Matching (PSM) Analysis

Considering the varying levels of digital transformation, whether companies adopt digital transformation strategies to enhance green innovation also depends on their strategic objectives. To mitigate potential endogeneity, this study first categorizes firms that experienced digital transformation during the reporting period as the experimental group, while those that did not undergo digital transformation are categorized as the control group. A dummy variable, digitdum, is created, with firms that underwent digital transformation assigned a value of 1 and those that did not assigned a value of 0. Subsequently, a propensity score matching (PSM) approach is employed to conduct robustness checks.

This paper matches the two sample groups on criteria including company size (Size), years since establishment (Age), debt-to-asset ratio (Lev), return on assets (ROA), ownership concentration (Shconcern), risk resistance ratio(ReAssets), firm growth (TQ), government subsidies (Subsidy), and board size (Boardsize) using a 1:1 nearest neighbor matching technique. This is done to ensure that the two sample groups are nearly identical in characteristics, thus allowing any differences between them to reflect solely the impact of digital transformation. The reliability of the propensity score matching method can be assessed by observing the absolute values of the standard deviations of the matched variables; a smaller absolute standard deviation indicates better matching efficacy. Table 7 presents the results of the sample balance test. It demonstrates that the absolute values of the standard deviations for both the experimental group and the control group are within 5%, thus meeting the specified requirements. The test results indicate that the majority of control variables show no significant differences in their matched characteristics. This affirms the acceptance of the null hypothesis that the means of the matched variables are equal post-matching, suggesting that the results following PSM are reliable. As shown in Table 8, the average treatment effect (ATT) test results are reported, indicating that the ATT value for the response variable post-matching is positive, with the t-value passing the 1% significance level test, highlighting a significant average treatment effect in the experimental group.

Table 7: Comparison of Sample Characteristics Before and After PSM Matching

Variable	Unmatched Matched	Mean Treated	Control	% bias	% reduct |bias|	t-test t	p > |t|
Size	U	22.219	22.01	16.5	96.7	8.08	0.000
	M	22.219	22.212	0.5		0.64	0.523
Age	U	18.714	17.802	16.5	83.5	7.83	0.000
	M	18.712	18.561	2.7		3.32	0.001
Lev	U	.41115	0.42991	-8.9	78.3	-4.57	0.000
	M	.41117	0.40709	1.9		2.33	0.020
ROA	U	.03598	0.02896	7.7	89.0	3.81	0.000
	M	.03613	0.03536	0.8		1.13	0.020
Shconcern	U	.59375	0.57547	11.9	87.3	6.03	0.000
	M	.5937	0.59602	-1.5		-1.84	0.065
TQ	U	2.0290	2.1298	-7.1	96.6	-3.79	0.000
	M	2.0296	2.0262	0.2		0.31	0.758
ReAsset	U	.17756	0.13785	18.9	90.8	10.04	0.000
	M	.17755	0.18121	-1.7		-2.27	0.023
Subsidy	U	4.7286	4.1915	19.3	96.5	9.52	0.000
	M	4.7266	4.6636	2.2		0.84	0.403
Boardsize	U	8.4334	8.5736	-8.6	98.0	-4.42	0.000
	M	8.4337	8.3793	-0.2		-0.21	0.836

Table 8: ATT Treatment Effect

Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
Ginnov	Unmatched	.813801518	.451949036	.361852482	.022002295	16.45***
	ATT	.813412538	.502088407	.311324131	.023079022	13.49***
Ginvia	Unmatched	.532040631	.260510644	.271529987	.017370223	12.81***
	ATT	.531733859	.298231896	.233501963	.017225857	13.56***
Gumia	Unmatched	.542758994	.320248414	.22251058	.017370223	12.81***
	ATT	.542550365	.352025542	.190524823	.018344556	10.39***

Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Regression results for the samples after PSM processing are shown in Table 9. As observed from columns (1) and (2), the regression coefficient of Digit is significantly positive at the 1% level, consistent with the previous results. This implies that even after controlling for endogeneity issues, the conclusions drawn earlier remain robust. That is, digital transformation significantly promotes green innovation, substantive innovation, and strategic innovation, and the main effect of this study is not affected by sample selection bias.

Table 9: Analysis of PSM Regression Results

	(1)	(2)	(3)
	Ginnov	Ginvia	Gumia
Digit	0.085***	0.078***	0.038***
	(0.010)	(0.008)	(0.008)
Controls	Yes	Yes	Yes
N	5105.000	5105.000	5105.000
Time	Yes	Yes	Yes

Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

4.4 Heterogeneity analysis

4.4.1 Regional Heterogeneity Analysis

There are significant differences in factor endowments, environmental conditions, and economic foundations across various regions in China. According to theories in strategic management and industrial organization, enterprises' strategic decisions are strongly influenced by the external environment and the structural characteristics of the industries in which they operate. Wu et al. (2021) identified substantial regional disparities in the impact of the digital economy. Currently, the digital economy exhibits pronounced regional variations, particularly in terms of digital infrastructure development and the adoption of digital technologies. Zhang et al. (2023) further argue that regional green development processes are closely tied to government environmental policies.

To explore these regional differences, this study divides the research sample into three regions: eastern, central, and western China. The empirical analysis results are presented in Table 10. Columns (1) and (3) show that the digital economy has a significant positive impact on green innovation in both the eastern and western regions, with a significance level of 1%. The eastern region, with its advanced economic conditions, abundant human resources, and favorable geographic advantages, provides an environment conducive to digital empowerment and innovation. In contrast, the western region has benefited from policy incentives such as the "Eastern Data Western Calculation" initiative, which has spurred digital development and contributed to positive outcomes in green innovation. Column (2) demonstrates that digital transformation has a significant impact on corporate green innovation in the central region at the 10% significance level. However, intense industrial homogenization in the central region has led to fierce local competition, with municipalities replicating central government industrial policies in efforts to attract resources.

This analysis highlights the importance of considering regional heterogeneity in evaluating the effects of the digital economy on green innovation. The findings suggest that region-specific strategies may be necessary to foster digital development and drive sustainable innovation across different parts of China. Differences in factor endowments, environmental conditions, and economic foundations exist among various regions in China. According to theories in strategic management and industrial organization, enterprises' strategic decisions are heavily influenced by the external environment and the industry's structural characteristics in which they operate. Wu et al. (2021) identified substantial regional disparities in the impact of the digital economy. Currently, the digital economy exhibits notable regional variations, including differences in digital infrastructure development and the extent of digital technology adoption across regions. Zhang et al. (2023) argue that regional green development processes are closely linked to government environmental policies.

To investigate these regional differences, this study divides the research sample into eastern, central, and western regions of China. Empirical analysis results are presented in Table 10. Columns (1) and (3) indicate that the digital economy has a significant positive effect on green innovation in both the eastern and western regions at the 1% significance level. The eastern region benefits from developed economic conditions, abundant human resources, and favorable geographical advantages, which encourage enterprises to actively pursue digital empowerment and innovation. In the western region, policy incentives such as the "Eastern Data Western Calculation" initiative have bolstered digital development, contributing to positive outcomes for green innovation. Column (2) reveals that digital transformation in the central region significantly impacts corporate green innovation at the 10% significance level. However, intense industrial homogenization in the central region leads to fierce local competition, with municipalities replicating central industrial policies to attract resources.

Table 10：Regional Heterogeneity

	(1)	(2)	(3)
	East	Central	West
	Ginnov	Ginnov	Ginnov
Digit	0.061***	0.049*	0.075***
	(0.009)	(0.019)	(0.021)
Controls	Yes	Yes	Yes
r2	0.180	0.182	0.138
Time	Yes	Yes	Yes

Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

4.4.2 Industry Heterogeneity Analysis

In recent years, China has actively promoted green and low-carbon development, leading to increasingly stringent environmental regulations on heavily polluting enterprises. As a result, firms operating in heavily polluting industries may exhibit a stronger willingness and motivation to pursue green innovation. This study hypothesizes that the positive impact of digital development on green innovation is likely to be more pronounced for enterprises in heavily polluting industries.

To assess industry heterogeneity, this study categorizes industries into two groups: non-heavily polluting industries and heavily polluting industries. The classification follows the "List of Classification and Management of Environmental Protection Check Industries for Listed Companies" issued by the Chinese Ministry of Environmental Protection in 2008.

The regression results presented in Table 11 illustrate the differential impact of industry classification on the relationship between enterprise digital transformation and green innovation. The findings reveal that, regardless of whether an enterprise belongs to a heavily polluting industry, digital transformation significantly promotes green innovation. However, the magnitude of this effect may vary depending on the industry's environmental profile, suggesting that digital development plays a crucial role in driving green innovation across a broad spectrum of industries.

These results underscore the need for industry-specific approaches to foster digital transformation and sustainable innovation, particularly in sectors facing stringent environmental regulations.

Table 11: Industry Heterogeneity Analysis

	(1)	(2)
	Heavy Polluting	Non-Heavy Polluting
	Ginnov	Ginnov
Digit	0.057***	0.060***

	(0.011)	(0.007)
Controls	Yes	Yes
r2	0.136	0.163
Time	Yes	Yes

Standard errors in parentheses * p < 0.1, ** p < 0.05, *** p < 0.01

4.5 Mechanism Analysis

To verify the mechanism of corporate governance, it is first necessary to construct the corporate governance variables. In this paper, Principal Component Analysis (PCA) is used to construct the corporate governance variable. According to Lu and Dang(2012), corporate governance primarily includes three aspects: shareholders, the board of directors, and incentive mechanisms. So this paper selects nine indicators from three categories, selecting the first principal component as the variable measuring the corporate governance (Govern) after PCA. The indicators are shown on table 12.

Table 12：Construction of Corporate Governance Indicator

Category	Sub-category
Shareholders	The proportion of control of the listed company owned by the actual controller
	The balance of equity (the proportion of shares held by the second to tenth largest shareholders/the proportion of shares held by the first largest shareholder)
	The proportion of institutional shareholding
Board	Board independence(the ratio of the number of independent directors to the total number of directors)
	Board size
	Whether the Chairman and Chief Executive Officer（CEO）are combined (1 if the two positions are combined, 0 otherwise)
	Supervisory board size
Incentive and constraint mechanism	Payment concentration (total pay of the top three management/total pay of the management)
	The proportion of management shareholding

Using a mediation effects model, this study analyzes the mechanism of the impact of the digital transformation on green innovation. In this model, corporate governance, constructed as the mediating variable. The regression result is presented in table 13. There is a positive correlation between digital transformation and corporate governance, and this correlation is significant. The coefficient of this variable is 0.007, and the regression results are significant at the 5% level. The regression results indicate that digital transformation significantly enhances corporate governance, thus verifying the transmission mechanism by which digital transformation improves green innovation efficiency through enhancing corporate governance. This supports hypothesis H3.

Table 13: Regression Results of Mechanism Analysis

	(1)
	Govern
Digit	0.007**
	(0.003)
Controls	Yes
N	32286.000
r2	0.044
Time	Yes

Standard errors in parentheses * p < 0.1, ** p < 0.05, *** p < 0.01

5 Conclusions

This paper investigates the impact of enterprise digital transformation on green innovation at the micro level. The findings indicate that digital transformation significantly promotes green innovation within enterprises, with a more pronounced effect on substantive innovation compared to strategic innovation. In analyzing the underlying mechanisms, principal component analysis (PCA) is employed to construct corporate governance indicators as mediating variables, thereby verifying the mediating effect of corporate governance. Additionally, the research sample is further categorized based on regional and industrial distinctions.

The empirical results reveal several key insights: First, digital transformation notably enhances green innovation, particularly substantive green innovation. Second, the positive effect of digital transformation on green innovation is more significant in both eastern and western regions. Regardless of whether enterprises operate in heavily polluting industries, digital transformation serves as a catalyst for green innovation. Third, the mechanism analysis results suggest that corporate digital transformation fosters green innovation by strengthening corporate governance.

Based on these findings, several policy recommendations are proposed:

1. Leverage Government Support for Digital Transformation and Green Innovation: The government should play an active role in promoting digital transformation and green innovation. Guided by policy frameworks, there should be an emphasis on enhancing digital infrastructure to facilitate enterprise digital transformation. A robust digital infrastructure is critical for supporting industrial structures, economic development, and ecological sustainability. Therefore, China should increase investments in digital infrastructure, strengthen the digital ecosystem, establish unified standards, and promote interoperability of information.

Furthermore, the government must accelerate the formulation and revision of laws and regulations suitable for the digital economy, refining the governance system. This includes establishing a comprehensive data security management framework, strengthening the protection of intellectual property related to digital technology and green innovation, and providing favorable policies to support enterprise development.

2. Facilitate the Transmission Mechanism of Digital Technology: To assist companies in deepening their digital transformation, it is essential to address barriers that discourage transformation due to high costs, long implementation cycles, and potential disruptions. This can be achieved by improving government information disclosure systems, maintaining policy continuity, and implementing differentiated policies tailored to industries of varying scales, sectors, and characteristics, while respecting the natural progression of enterprise development. The government should consider providing subsidies for significant breakthroughs in digital transformation and green innovation, thereby promoting integrated digital and green development through financial support, tax incentives, and government procurement of services.

3. Encourage Enterprises to Embrace Green Development within Digital Transformation: Enterprises should capitalize on the opportunities presented by digital transformation to foster a green development mindset. The digital economy is reshaping industry ecosystems and influencing future business models and directions. Companies should leverage digital technologies to mitigate information asymmetry, enhance information transparency, and improve corporate governance while promoting green development. This can be achieved by accelerating the development of data-sharing and integration platforms to reduce information asymmetry between internal and external stakeholders and improve disclosure quality.

By utilizing digital technologies, businesses can support new business development and facilitate the transformation of traditional operations, modernizing production methods to achieve increased intelligence and automation. Additionally, enterprises can harness big data and artificial intelligence to drive decision-making, identify potential opportunities for green innovation, optimize resource consumption and production processes, and formulate more precise strategies for green development.

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