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RESEARCH ARTICLE

Digital Transformation and Green Technology Innovation in Manufacturing Enterprises: A Study Based on Big Data Text Mining*

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Abstract

Digital transformation serves as a new driving force and engine for enterprise innovation. Meanwhile, the national strategy of carbon peaking and carbon neutrality has set new goals and requirements for the green development of the Chinese manufacturing industry. From the three-dimensional perspective of "strategy–resource–institution," this paper explores the impact and mechanism of digital transformation on green technology innovation of Chinese manufacturing enterprises and the heterogeneous impact of the institutional logic of ownership structure. Using a sample of 1,016 A-share listed manufacturing companies on the Shanghai and Shenzhen Stock Exchanges from 2011 to 2019 and based on big data text mining and a negative binomial regression model, this study finds that: (1) Digital strategy significantly enhances green technology innovation capability of enterprises; (2) digital resource investment partially mediates the effect of digital strategy on the enhancement of green technology innovation capability; and (3) the ownership structure of enterprises plays a moderating role in the mediating relationship mentioned above. Specifically, compared to state-owned enterprises (SOEs), non-state-owned enterprises (NSOEs) show no significant difference in the stages where digital strategy promotes green technology innovation and guides digital resource investment. However, they demonstrate higher efficiency in transforming digital resource investment into green technology innovation. The robustness test indicates that the significant effect of digital strategy and resource investment on green technology innovation in enterprises remains valid in the medium term, with a continuous enabling effect. There is no significant difference between SOEs and NSOEs in the medium and long term in promoting green technology innovation through digital transformation. Further, introducing keyword text networks to explore the structural impact of digital strategy, this study finds that digital product and manufacturing strategy are adequate strategic dimensions to enhance green technology innovation capability, and digital financial strategy and digital marketing strategy have no direct promoting effect on green technology innovation of enterprises. From the perspectives of strategies, resources, and institutions, the research findings elucidate the process mechanisms of digital acceleration in the green transformation of manufacturing and the heterogeneous effect of ownership structure and provide critical theoretical insights into the role mechanisms and contextual factors

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of digitalization on green innovation in manufacturing enterprises. Moreover, this study offers scientific decision-making support for incentivizing the manufacturing industry to seize the opportunities of industrial digitalization and accelerate carbon peaking and carbon neutrality.

Keywords digital transformation; carbon peaking and carbon neutrality; green technology innovation; strategy; resource-based view (RBV)

1 Introduction

Digital transformation is a key issue in the new wave of the global technological and industrial revolution, and it serves as an important lever for promoting high-quality development in the new journey toward Chinese modernization (Liu et al., 2020; Yin et al., 2022; Yu et al., 2017). Meanwhile, the goals of carbon peaking and carbon neutrality have become a new strategic objective and mission for the green transformation of China's economy and society in the new development stage. The historical convergence of digital transformation and green transformation presents new opportunities and challenges for enterprises to seize the strategic window of digitalization and accelerate digital innovation aimed at green and sustainable development. Research by the International Energy Agency (IEA) (2021) indicates that demand-driven solutions based on digital technologies will provide significant benefits in terms of cost reduction and efficiency improvement in energy use, as well as reducing carbon emissions. However, the substantial carbon emissions generated by digital technologies and their application in digital transformation have also led to skepticism and controversy regarding green transformation solutions based on digital technologies. For example, the results of nearly 170 international studies on the environmental impact of digital technology conducted by the Shift Project[1], a European think tank, show that in 2018, digital technologies accounted for 3.7% of global carbon dioxide emissions, surpassing the 2.5% share of the aviation industry, and this proportion continues to rise rapidly.

The advantages and disadvantages of digital transformation in relation to green transformation have become a highly debated topic among scholars and industry professionals alike. This study focuses on the digital transformation and green technology innovation of manufacturing enterprises and addresses the following four interrelated and cohesive questions: (1) Can digital strategy effectively promote green technology innovation in enterprises? (2) What is the relationship between corporate digital strategy and digital resource investment, and how do they influence green technology innovation? (3) In the context of China's ongoing market-oriented reforms of state-owned enterprises (SOEs), what are the heterogeneous effect of corporate ownership structure on this process? (4) Do different dimensions of digital strategy have varying effects on green technology innovation? Using a sample of China's A-share listed manufacturing companies from 2011 to 2019, this study systematically explores the effect of digital transformation strategy on the green technology innovation capability of Chinese manufacturing enterprises through econometric

[1] The Shift Project is a French non-profit think tank advocating for the transition to a post-carbon economy. It is dedicated to serving the public interests through scientific and objective research, influencing, and providing decision-making support for the European energy transition.

analysis methods such as big data mining and negative binomial regression, and from the dual perspectives of strategy and resource. This study also introduces digital resource investment to reveal the underlying mechanism between these two factors. Based on the resource-based view (RBV), it examines the heterogeneous effect of corporate ownership structure on the transformation process from digitalization to green technology innovation. It further employs text network analysis to deconstruct digital strategy and reveal the differential relationships between different dimensions of digital strategy and green technology innovation in manufacturing enterprises.

This study makes three significant contributions to the theory and practice of synergistically advancing digital and green transformations. (1) From the dual perspectives of resource and strategy, this study uncovers the "black box" of how digital strategy enhances the green technology innovation capability of manufacturing enterprises. It employs the process logic of "strategic design–resource investment–innovation development," combined with big data mining and econometric empirical analysis. It provides empirical evidence from a micro perspective on the effect of digital transformation on green technology innovation, thereby offering new insights into digital innovation management from the perspective of carbon peaking and carbon neutrality. (2) By introducing corporate ownership structure, the study explores its heterogeneous effect on green technology innovation driven by digitalization. From the consistency and timeliness of the "strategy–action" alignment in digital transformation, it is evident that Chinese manufacturing enterprises generally achieve a unity of knowledge and action in digital transformation and that digital transformation profoundly influences green technology innovation. However, in the short term, SOEs are less efficient in converting digital resources into green technology innovation compared to non-state-owned enterprises (NSOEs), while there is no significant difference between the two in the medium and long term. This finding reflects the positive reform outcomes of SOEs in green development and provides managerial insights for them to further seize opportunities for digital transformation, improve the efficiency of internal digital resource conversion, and contribute to China's green and sustainable development. (3) Through text network analysis, the study deconstructs digital strategy and finds that digital finance and digital marketing strategies do not have a substantial influence on the green technology innovation capability of enterprises. In contrast, digital product and manufacturing strategies are effective strategic dimensions for enhancing green technology innovation capability. This indicates that the digital transformation of China's manufacturing industry needs to place greater emphasis on the digitalization of new product development and manufacturing processes and increase resource investment to maximize the enabling effect of digitalization on the green development of the manufacturing industry.

2 Research Hypotheses

2.1 Digital Strategy and Green Technology Innovation in Enterprises

In the digital economy era, the technological and industrial revolution driven by digital technologies such as artificial intelligence (AI), big data, cloud computing, and Internet of Things (IoT) is rapidly reshaping the internal and external environments of enterprises. The

competitive landscape in which enterprises operate has become more complex, volatile, and uncertain (Yin et al., 2019a, 2019b). Digital transformation, as a crucial strategic opportunity for upgrading and reshaping competitive advantages, must be incorporated into the top-level strategic design of enterprises. This approach is essential to effectively address the challenges of organizational restructuring, human resource management, and corporate culture reconstruction encountered during the digitalization process, thereby accelerating the innovation and transformation of enterprises (Chen et al., 2020).

The essence of carbon neutrality is the developmental transition from resource dependency to technology dependency, and its strategic window of opportunity coincides with the convergence of three trends: the pursuit of building China into a leading country in science and technology, digitalization, and carbon neutrality. There is a historical inevitability to the interaction between the two national strategies of digital and green transformations. As a core component of green innovation, green technology innovation is a crucial path for enterprises to achieve green innovation, and this technological innovation is profoundly influenced by digital strategy. As previously discussed, digital transformation is a vital lever for China to break free from the path dependency of high-carbon development and to accelerate the transition to a green, low-carbon development model. Enterprises that integrate digital transformation into their overall organizational management and operational strategies are likely to have more potential to efficiently utilize digital technologies and data factors to enhance digital R&D efficiency, thereby more effectively boosting green technology innovation capability and achieving green development goals. On this basis, the following hypothesis is proposed.

H1: An enterprise's digital strategy can significantly enhance its green technology innovation capability.

2.2 The Mediating Effect of Digital Resource Investment

While the relationship between digital strategy and corporate innovation development has attracted much attention, little is known about its underlying mechanisms, the relationship between strategies and resources during the transformation process, and issues related to their alignment. Bouncken and Barwinski (2020) reveal that an enterprise's commitment to digitalization, under the guidance of a clear strategy, spreads within the organization through common values and enthusiasm for changes, thereby enhancing the functionality of digital technologies within the company. Both the RBV and the dynamic capability view (DCV) emphasize the interplay between strategies and resources. From the RBV perspective, Barney (2001) suggests that companies achieve sustainable strategic advantages by learning how to leverage their resources to implement strategies and outlines two strategic implementation paths under the RBV. The first path emphasizes the company's strategic implementation capability as a resource that can bring long-term competitive advantages. The second path says that using strategies based on current resources does not give you a long-term competitive edge. Instead, it works with other valuable, rare, inimitable, and non-substitutable resources as a strategic complement. From the perspective of DCV, the

realization of an enterprise's potential resource value mainly depends on the implementation of strategies and the ways resources are utilized under these strategies (Barney & Arikan, 2005; Hitt et al., 2001; Newbert, 2007). Digital transformation is a long-term process, and currently, there is no fixed model for digital transformation across industries. Top-level design at the strategic level requires actual resource investment to effectively identify, absorb, and transform internal and external technological and R&D opportunities and knowledge into dynamic capability. To cope with external competitive pressures and policy pressures, enterprises emphasizing digital strategy will guide corresponding digital resource investments to accelerate green transformation. On this basis, the following hypothesis is proposed.

H2a: An enterprise's digital strategy can significantly drive its digital resource investment.

The RBV posits that an enterprise's competitive advantage stems from its heterogeneous internal resources and organizational capabilities. In the static operational phase, digital resources can facilitate the alignment of materials and technology, thus achieving the required innovation. In the dynamic evolution phase, digital resources can effectively absorb and utilize information, reconfigure and integrate resources, and develop the combinatory skills necessary for green technology innovation. This enables enterprises to adapt to the constantly changing environment and achieve sustainable survival (Huang & Li, 2017). Through the analysis of 11 case studies, Melander and Pazirandeh (2019) point out the positive impact of digital resource utilization on environmental sustainability from the perspective of extended networks. Digitalization plays at least two roles in the collaborative green innovation process within enterprises' networks. First, innovations based on digitalization and big data technology can improve the sustainability of products and services, such as energy consumption visualization technology and energy efficiency improvement technology enabled by digital software. Second, in the digital era, the sharing of data and technology can stimulate enterprise vitality and promote collaborative innovation. Digital technologies also lay the foundation for technological exchanges between different enterprises. For instance, entities such as automobile manufacturers, maintenance providers, battery suppliers, and product users, integrate their innovation functions through built-in digital platforms and data sharing within products. This integration reduces the cost of green technology innovation, speeds up the process, and enhances effectiveness.

On this basis, the following hypothesis is proposed.

H2b: An enterprise's digital resource investment further strengthens its green technology innovation capability.

Furthermore, based on the deductions from *H2a* and *H2b*, the increase in digital resource investment induced by digital strategy will further enhance green technology innovation capability, indicating that digital resource investment serves as a mediator in this relationship. Accordingly, the following hypothesis is proposed.

H2c: Digital resource investment mediates the relationship between an enterprise's digital strategy and its green technology innovation capability.

2.3 The Moderating Effect of Corporate Ownership Structure

The institution-based view (IBV) posits that an enterprise's strategic behavior or choices are significantly influenced by institutional factors. Corporate innovation activities, particularly green innovation, as strategic choices, are also influenced by corporate resources and institutional factors. Many scholars believe that corporate green innovation is distinct from general innovation activities. It cannot be adequately explained solely from the perspectives of technology and market; instead, it should also be considered from aspects such as organizational attributes and regulations. Rennings et al. (2006) indicate that environmental product innovation is primarily driven by market factors, whereas environmental process innovation is more influenced by environmental regulations. In the context of China's transitional period, the differences in ownership structure imply varying degrees of government support, which directly affects corporate innovation behavior. Furthermore, enterprises with different ownership structures differ in their goal orientation, operational modes, and other aspects, which can affect organizational performance and have direct or indirect impacts on green technology innovation.

Based on the principal-agent theory, the separation of ownership and management brings a series of issues to modern enterprises. Compared to NSOEs, SOEs face more pronounced agency problems (Pan & Yu, 2011). For the executives of SOEs, the adherence to government policies is part of their performance evaluation criteria, along with enterprises' financial performance. Green innovation, particularly in an industry-wide immature state, requires substantial upfront investment. The returns on these investments, however, take a considerable amount of time to materialize, and the outcomes of corporate innovation are highly uncertain. Consequently, current executives may prefer to avoid risks to prevent tarnishing their records and leave a positive legacy for their successors. In such scenarios, these executives lack the motivation to utilize existing digital resources for green innovation activities compared to NSOEs. When SOEs face difficulties, they are more likely to secure government support in the form of capital, subsidies, tax reductions, and other supportive policies and funds (Li & Tao, 2013). This lack of internal and external pressure can stifle SOEs' intentions and actions toward high-risk, high-investment, and long-term exploratory innovation activities, including digital transformation and green technology innovation.

Based on the above considerations, the following hypotheses are proposed.

H3a: Ownership structure negatively moderates the effect of an enterprise's digital strategy on its green technology innovation capability.

H3b: Ownership structure moderates the effect of an enterprise's digital strategy on its digital resource investment. Specifically, compared to SOEs, the ownership structure of NSOEs strengthens the relationship between their digital strategy and digital resource investment.

H3c: Ownership structure moderates the effect of an enterprise's digital resource investment on its green technology innovation capability. Specifically, compared to SOEs, the ownership structure of NSOEs strengthens the relationship between their digital resource investment and green technology innovation capability.

Figure 1 illustrates the research framework of this study.

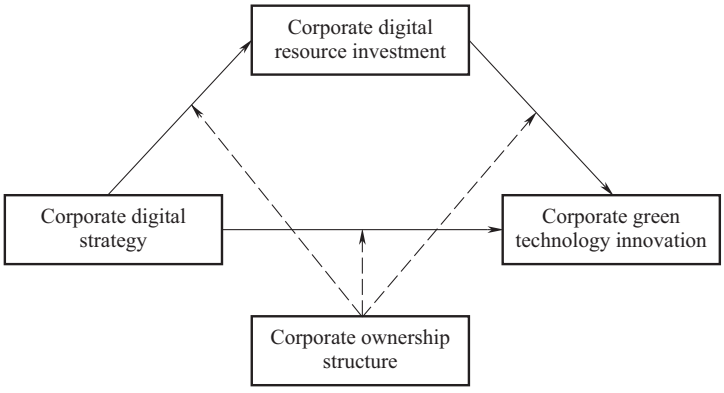

Figure 1 Research Framework

3 Research Design

3.1 Research Sample and Data Sources

Considering the varying effects of different industry characteristics on corporate digital strategy and the disruptive impact of the COVID-19 pandemic in 2020 on industrial and enterprise development, this study selects manufacturing companies listed on the Shanghai and Shenzhen Stock Exchanges from 2011 to 2019 as the sample. The annual report text data used in this study are sourced from the official websites of the Shanghai Stock Exchange and Shenzhen Stock Exchange. Patent data are obtained from the National Intellectual Property Administration's database, and other data are sourced from the China Stock Market and Accounting Research (CSMAR) database. Samples with missing key variables are excluded, while enterprises with zero or missing data for certain years but non-zero data for other years are retained. The final effective sample consists of 1,016 manufacturing enterprises, with a total of 4,166 observations. All micro-level data in this study are winsorized at the 1% and 99% levels.

3.2 Definition and Measurement of Key Variables

3.2.1 Explanatory Variable

Referring to the methods of Wu et al. (2021) and Qi and Cai (2020), we develop the digital strategy index through content analysis based on big data mining. First, annual reports of Chinese A-share listed companies on the Shanghai and Shenzhen Stock Exchanges from 2011 to 2019 are downloaded using a web crawler. The pdfminer3k library in Python is then used to convert all PDF-format annual reports into a text format. For reports that cannot be converted, the optical character recognition technology interface provided by Baidu AI Cloud is utilized for format conversion. Following this, the jieba library in Python is used to segment all the text. Based on existing research and discussions with experts in relevant fields, a bag of words (see Figure 2) that aligns with digital strategy is selected and further refined using keyword co-occurrence network analysis. Finally, the total frequency of keywords in the bag of words is recounted. Due to the large total number of keyword frequencies and their

evidently skewed distribution, the natural logarithm of the keyword frequencies is used to develop the digital strategy index.

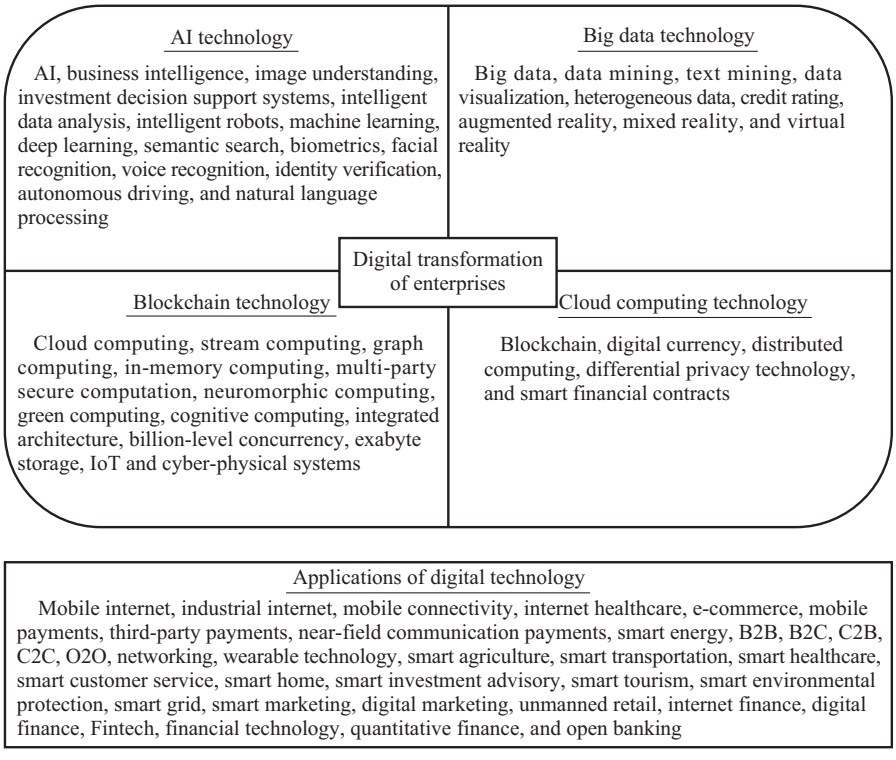

Figure 2 The Bag of Words of Corporate Digital Strategy
Source: Adapted from Wu et al. (2021).

3.2.2 Mediating Variable

The core component of digital resource investment involves investments in digital technology-related equipment and systems, including but not limited to computer terminals, sensors, storage devices, monitoring equipment, and information technology systems as digital software resources. Digital investment and digital technology outsourcing are two critical indicators of the implementation status of an enterprise's digital strategy, with internal digital technology competence serving as the direct foundation for an enterprise's digital transformation and sustainability (Mithas et al., 2013; Nwankpa & Merhout, 2020). Referring to the study by Dewan et al. (2007), we define digital resource investment as the sum of all items containing "computer" and "electronic" in the fixed assets section of financial statements. The natural logarithm of this sum is used to develop the digital resource investment index.

3.2.3 Dependent Variable

Following the research by Qi et al. (2018), we adopt the classification of green patents according to the *United Nations Framework Convention on Climate Change*, which includes

seven categories: transportation, waste management, energy conservation, alternative energy production, administrative regulatory or design aspects, agriculture or forestry, and nuclear power generation. Based on this classification standard, the number of green patents for each enterprise per year is calculated using the National Intellectual Property Administration's database. Furthermore, a distinction is made between green invention patents and green utility model patents, which serve as indicators of an enterprise's green technology innovation capability. It is generally believed that the level of innovation in patents is considered to decrease in the following order: invention patents, utility model patents, and design patents. In the main test, we use the number of green invention patent applications, which lags one year behind the digital strategy, to measure an enterprise's green technology innovation capability. In the robustness test, the sum of green invention patent applications and green utility model patent applications is used as an alternative variable of green technology innovation capability.

3.2.4 Moderating Variable

Chinese enterprises can be categorized into four types based on the actual controllers of their publicly traded shares: SOEs, NSOEs, foreign-owned enterprises, and other enterprises. In this study, the ownership structure of enterprises is determined by the type of actual controller recorded in the CSMAR database. Some enterprises in the CSMAR database are labeled with multiple ownership types. Upon collecting public information, it is confirmed that these companies indeed have a mixed ownership structure, with no single ownership type holding an absolute majority. To avoid the influence of these enterprises on the research results, companies marked as having multiple ownership types are excluded from the sample. Only those clearly identified as SOEs or NSOEs are retained. An ownership dummy variable, *SOE*, is constructed, with SOEs marked as 1 and NSOEs marked as 0.

3.2.5 Other Control Variables

Referring to Qi et al. (2018), a series of economic characteristics of enterprises are used as control variables in the model. Total revenue (logged, represented as *Rev*) and Tobin's *Q* (*TobinQ*) are used to measure the social wealth creation capacity of enterprises. The leverage ratio (*Lev*) of listed companies is used as a control variable to measure their credit evaluation. Net assets and the number of employees of the sample enterprises are used as control variables to measure the size of these enterprises, which are logged and represented as *Size* and *Labor*, respectively. R&D investment is a major determinant of innovation capability or output improvement, and the scale of innovation investment varies among enterprises and directly affects their innovation outputs. To highlight the heterogeneity in digital resource construction and avoid the influence of general differences in R&D investment scales among different enterprises on the research conclusions, R&D investment by listed manufacturing companies in the sample is selected as a control variable, which is logged and denoted as *RD*.

3.3 Descriptive Statistics and Group Tests

The results of the descriptive statistics are shown in Table 1. The dependent variable, green technology innovation performance, has an average value of 1.142, with a maximum of 235 and a minimum of 0, indicating a significantly skewed distribution that remains non-normal even after logging. This implies that a general Ordinary Least Squares regression (OLS) model is not suitable for exploring green patents. In addition, the standard deviation is 6.999, with a variance much larger than the mean, suggesting considerable individual differences in the level of green technology innovation among Chinese manufacturing enterprises. This also indicates that overdispersion needs to be considered when selecting the econometric model.

Table 1 Definition and Descriptive Statistics of Key Variables

Variable	(1) Observations	(2) Mean	(3) SD	(4) Max.	(5) Min.
DIG_STA	4,166	1.230	1.328	5.835	0
DIG_INV	4,166	2.767	0.229	3.114	0
GREEN_INN	4,166	1.142	6.999	235.000	0
Rev	4,166	21.310	1.287	27.530	15.180
Lev	4,166	0.385	0.195	0.989	0.049
TobinQ	4,166	2.008	1.163	8.705	0.884
Size	4,166	21.910	1.127	27.390	17.810
Labor	4,166	7.722	1.097	11.030	3.584
RD	4,166	17.860	1.397	25.030	8.337
SOE	4,166	0.239	0.427	1	0

Furthermore, considering the ownership structure of the sample enterprises, the ratio of SOEs (n = 222) to NSOEs (n = 794) in the study sample is approximately 1:3.5. A t-test of the mean values of the core variables, as shown in Table 2, reveals that the average green technology innovation performance of SOEs is about 0.259 higher than that of NSOEs, though this difference is not statistically significant. The mean value of the digital strategy for SOEs is 2.28 lower than that of NSOEs, and this difference is statistically significant at the 1% level. Conversely, the average digital resource investment of SOEs is approximately 0.33 higher than that of NSOEs, which is also significant at the 1% level. The preliminary findings indicate that there is no significant difference in green innovation development between SOEs and NSOEs. However, in digital transformation, SOEs are somewhat weaker than NSOEs in terms of digital strategy but stronger in terms of digital resource investment. This descriptive statistic indicates significant differences in digital transformation between SOEs and NSOEs. It also demonstrates the necessity of considering ownership structure when exploring the relationship between digital transformation and green technology innovation.

Table 2 *t*-Test of Mean Differences between SOEs and NSOEs

Variable	Mean (SOEs, n = 222)	Mean (NSOEs, n = 794)	Pr ($\|T\| > \|t\|$)
GREEN_INN	1.338	1.079	0.309
DIG_STA	1.056	1.284	0.000***
DIG_INV	2.792	2.759	0.000***

Note. *** $p < 0.01$.

3.4 Models

Previous research on patents primarily relies on general linear or nonlinear regression models, which assume that random variables follow a normal distribution. However, due to the inherent characteristics of patent output, it is more appropriate to consider it as following a Poisson distribution. In this case, the use of general linear or nonlinear regression models to estimate equations under this assumption can lead to bias. In international studies, the Poisson distribution and the negative binomial distribution are the basic models used to examine patent output. However, the Poisson distribution model cannot address the issue of overdispersion, making it potentially unsuitable for studying green patent output. This study selects the appropriate model by examining whether the variance of the green technology innovation variable is much larger than the mean and whether the Alpha test result is significant. The specific tests are as follows: If the variance of the variable is approximately equal to the mean, it is discrete uniform, and a Poisson distribution model is used. If the variance is significantly greater than the mean and the Alpha test result is also significant, it indicates overdispersion, and a negative binomial distribution model is used. The statistical results show that the variance of green technology innovation (variance = 49) is much larger than the mean (Mean = 1.142). The Alpha tests conducted on all models in the study indicate that the negative binomial distribution model is superior to the Poisson distribution model (Likelihood Ratio Test of Alpha = 0).

In addition, considering the potential time lag in the effect of digital transformation on green technology innovation, the green technology innovation variable (*GREEN_INN*) is lagged by one period. Further lagged tests are conducted in the robustness test to verify the medium- and long-term effects of corporate digital transformation. This study controls for the dummy variables of year (*Years*) and industry (*Ind*) to account for the endogenous effects of economic cycles and industry heterogeneity on the key variables and their interrelationships.

To test *H1*, the following model (1) is constructed:

$$GREEN_INN_{t+1} = \beta_0 + \beta_1 DIG_STA_t + \beta_2 RD_t + \beta_3 Lev_t + \beta_4 Rev_t + \beta_5 TobinQ_t + \beta_6 Labor_t + \beta_7 Size_t + \sum Ind + \sum Years + \varepsilon. \quad (1)$$

Models (2)–(4) are constructed to test *H2a*, *H2b*, and *H2c*. Since all variables in model (2) are continuous variables that follow a normal distribution, a multiple linear regression model is used:

$$DIG_INV_t = \beta_0 + \beta_1 DIG_STA_t + \beta_2 RD_t + \beta_3 Lev_t + \beta_4 Rev_t + \beta_5 TobinQ_t + \beta_6 Labor_t + \beta_7 Size_t + \sum Ind + \sum Years + \varepsilon, \quad (2)$$

$$GREEN_INN_{t+1} = \beta_0 + \beta_1 DIG_INV_t + \beta_2 RD_t + \beta_3 Lev_t + \beta_4 Rev_t + \beta_5 TobinQ_t + \beta_6 Labor_t + \beta_7 Size_t + \sum Ind + \sum Years + \varepsilon, \quad (3)$$

$$GREEN_INN_{t+1} = \beta_0 + \beta_1 DIG_STA_t + \beta_2 DIG_INV_t + \beta_3 RD_t + \beta_4 Lev_t + \beta_5 Rev_t + \beta_6 TobinQ_t + \beta_7 Labor_t + \beta_8 Size_t + \sum Ind + \sum Years + \varepsilon. \quad (4)$$

Models (5)–(8) are constructed to test *H3a*, *H3b*, and *H3c*. In model (8), the independent variable (*DIG_STA*), the mediating variable (*DIG_INV*), and the moderating variable (*SOE*), along with the interaction term between the moderating variable and the mediating variable (*SOE×DIG_INV*), are included to further verify the presence of a moderated mediating effect. Since all variables in model (6) are continuous variables that follow a normal distribution, a multiple linear regression model is used:

$$GREEN_INN_{t+1} = \beta_0 + \beta_1 DIG_STA_t + \beta_2 SOE_t \times DIG_{STA_t} + \beta_3 SOE_t + \beta_4 RD_t + \beta_5 Lev_t + \beta_6 Rev_t + \beta_7 TobinQ_t + \beta_8 Labor_t + \beta_9 Size_t + \sum Ind + \sum Years + \varepsilon, \quad (5)$$

$$DIG_INV_t = \beta_0 + \beta_1 DIG_STA_t + \beta_2 SOE_t \times DIG_STA_t + \beta_3 SOE_t + \beta_4 RD_t + \beta_5 Lev_t + \beta_6 Rev_t + \beta_7 TobinQ_t + \beta_8 Labor_t + \beta_9 Size_t + \sum Ind + \sum Years + \varepsilon, \quad (6)$$

$$GREEN_INN_{t+1} = \beta_0 + \beta_1 DIG_INV_t + \beta_2 SOE_t \times DIG_INV_t + \beta_3 SOE_t + \beta_4 RD_t + \beta_5 Lev_t + \beta_6 Rev_t + \beta_7 TobinQ_t + \beta_8 Labor_t + \beta_9 Size_t + \sum Ind + \sum Years + \varepsilon, \quad (7)$$

$$GREEN_INN_{t+1} = \beta_0 + \beta_1 DIG_STA_t + \beta_2 DIG_INV_t + \beta_3 SOE_t \times DIG_INV_t + \beta_4 SOE_t + \beta_5 RD_t + \beta_6 Lev_t + \beta_7 Rev_t + \beta_8 TobinQ_t + \beta_9 Labor_t + \beta_{10} Size_t + \sum Ind + \sum Years + \varepsilon. \quad (8)$$

In this model, β_0 represents the constant term; β_1, β_2, ⋯, and β_{10} are the coefficients of the variables; and ε denotes the residual term.

4 Hypothesis Test Results

The main empirical results are presented in Table 3. There is a positive and significant relationship between the digital strategy and green technology innovation at the 1% level ($\beta = 0.175$, $p < 0.01$) in column 1. This means that the digital strategy does encourage green technology innovation in enterprises, which supports *H1*. Columns (2) and (3) reveal that the coefficient of the digital strategy on digital resource investment is significantly positive ($\beta = 0.013$, $p < 0.01$), and the coefficient of digital resource investment on green technology innovation is also significantly positive ($\beta = 0.538$, $p < 0.1$). These findings support *H2a* and *H2b*, indicating that the digital strategy leads to increased digital resource investment, which in turn positively influences green technology innovation in enterprises. Following the mediating effect testing method by Wen et al. (2004), both the digital strategy and digital resource investment variables are included in the model. The results in column (4) show that the digital strategy's coefficient is still positive and significant. This means that digital resource investment partially mediates the effect of the digital strategy on green technology innovation, which supports *H2c*.

Further exploration of the effect of ownership structure is conducted. Columns (5) and (6) of Table 3 show that the coefficients for the interaction terms between ownership structure

Table 3 Main Test Results

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	GREEN_INN	*DIG_INV*	*GREEN_INN*	*GREEN_INN*	*GREEN_INN*	*DIG_INV*	*GREEN_INN*	*GREEN_INN*
DIG_STA	0.175***	0.013***		0.168***	0.145***	0.015***		0.166***
	(0.000)	(0.000)		(0.000)	(0.004)	(0.000)		(0.000)
SOE × *DIG_STA*					0.103	–0.009		
					(0.257)	(0.120)		
DIG_INV			0.538*	0.442			0.900***	0.807**
			(0.051)	(0.111)			(0.008)	(0.016)
SOE × *DIG_INV*							–1.104**	–1.119**
							(0.036)	(0.032)
SOE					–0.175	–0.019**	–0.140	–0.117
					(0.204)	(0.023)	(0.322)	(0.404)
RD	0.306***	0.022***	0.319***	0.299***	0.312***	0.022***	0.332***	0.311***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Lev	–0.555	–0.169***	–0.378	–0.462	–0.504	–0.167***	–0.471	–0.563
	(0.115)	(0.000)	(0.291)	(0.197)	(0.152)	(0.000)	(0.192)	(0.119)
Rev	–0.004	–0.002	0.056	–0.014	0.009	–0.000	0.109	0.036
	(0.974)	(0.837)	(0.675)	(0.918)	(0.947)	(0.988)	(0.423)	(0.790)
TobinQ	–0.029	–0.017***	0.032	–0.020	–0.028	–0.016***	0.033	–0.021
	(0.605)	(0.000)	(0.562)	(0.728)	(0.628)	(0.000)	(0.555)	(0.713)
Labor	–0.158*	0.031***	–0.171*	–0.161*	–0.153	0.031***	–0.202**	–0.190**
	(0.098)	(0.000)	(0.077)	(0.092)	(0.112)	(0.000)	(0.037)	(0.048)
Size	0.644***	0.038***	0.564***	0.628***	0.641***	0.040***	0.566***	0.629***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	–21.006***	1.476***	–22.180***	–21.574***	–21.349***	1.417***	–24.319***	–23.657***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	4,166	4,166	4,166	4,166	4,166	4,166	4,166	4,166
Industry fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.111	0.183	0.110	0.112	0.112	0.184	0.111	0.113

Note. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

and digital strategy are not significant. This indicates no significant difference between SOEs and NSOEs in the stages where digital strategy promotes green technology innovation and where digital strategy leads to digital resource investment, thereby rejecting *H3a* and *H3b*. Column (7) of Table 3 shows that the coefficient for the interaction term between digital resource investment and ownership structure is significant ($\beta = -1.104$, $p < 0.05$). This result indicates that, compared to NSOEs, SOEs are less efficient in converting digital resource investment into green technology innovation, thus supporting *H3c*.

The discrepancies between the empirical results and the theoretically derived hypotheses may stem from two main reasons. First, the logic behind how strategies and resources promote green technology innovation differs. Existing research, whether from the IBV or those considering ownership structure as a contingent factor, has not accounted for this difference. As a result, conclusions drawn from such studies might differ from the empirical findings of the present study. Second, according to the goal-orientation theory, in addition to achieving financial performance targets, SOEs also need to fulfill significant social responsibility goals (Hao et al., 2011). For general innovation activities, this complexity can lead to resource dispersion and negatively impact innovation behavior. However, as the main way for Chinese enterprises to promote the green development system of the economy, green technology innovation is highly consistent with the needs of China's construction of ecological civilization and modernized economic system. SOEs may have different behavioral logics in green technology innovation.

Based on the support for *H2c* and *H3c*, further examination is needed to test whether the ownership structure has a moderated mediating effect. Specifically, this involves exploring whether the digital strategy influences green technology innovation through the interaction between digital resource investment and ownership structure. Following the method for testing moderated mediating effects suggested in existing research, which involves "testing for moderating effects based on the mediating effect" (Wen et al., 2006), the previously proven mediating effect of digital resource investment is expanded by introducing the interaction term between digital resource investment and ownership structure in the model. The results in column (8) of Table 3 show that the coefficient for this interaction term is significantly negative ($\beta = -1.119$, $p < 0.05$). This indicates that ownership structure moderates the mediating effect of digital resource investment in the process where digital strategy promotes green technology innovation. In other words, NSOEs exhibit higher efficiency in the stage where digital resource investment is converted into green technology innovation.

5 Robustness Test

To account for the lagged effects of digital strategy and to further examine whether digital transformation provides enterprises with sustainable competitive advantages, in this study, both digital resource investment and green technology innovation performance are lagged by one year relative to digital strategy to test the medium-term effects of digital transformation. In addition, digital resource investment is lagged by two years relative to digital strategy, and green technology innovation performance lags four years behind digital strategy to test the

long-term effects. The results of the medium-term effects testing show that the conclusions drawn earlier remain unchanged. The long-term effects testing results indicate that digital resource investment continues to have a positive and significant effect on green technology innovation ($\beta = 0.014$, $p < 0.01$). However, the promoting effect of digital strategy on digital resource investment and the direct effect of digital strategy on technological innovation are positive but not significant. The diminishing effect of digital transformation over time reflects the intense competition and rapid technological iteration in digital strategy and digital infrastructure construction. Enterprises need to continuously update their digital strategy and infrastructure based on market conditions and technological advancements to maintain their own digital competitive advantages. Further considering the effect of ownership structure, the results show that there are no significant differences between SOEs and NSOEs in the medium- and long-term effects of digital transformation on green innovation across various stages.

The robustness test also takes into consideration the innovativeness of different types of patents. According to China's patent application regulations, invention patents must have "prominent substantive features and significant advancement," whereas utility model patents need only have "substantive features and advancement." Therefore, utility model patents are generally considered less innovative than invention patents. However, given that the green transition of Chinese enterprises is still in its initial stages and that some enterprises have limited levels of green technology innovation, they may not be able to produce high-level green technology innovations in a short period. Therefore, this robustness test considers both green invention patents and green utility model patents to measure the level of green technology innovation in enterprises. Descriptive statistics show that the average green technology innovation score is 2.274, with a maximum value of 413, a minimum value of 0, and a variance of 183.87, which is much larger than the mean. Further Alpha test indicates that the negative binomial distribution model is superior to the Poisson distribution model. When the negative binomial distribution model and the newly developed green technology innovation index are used to repeat the previous tests, all earlier conclusions remain unchanged.

In addition, the publication of Chinese patent applications is dynamic, requiring consideration of the time lag between the actual application and its publication. For example, among the invention patents published in July 2020, more than 15,000 were applied for in 2018. This situation can affect the accuracy of the green patent data used in this study. Therefore, all tests are repeated after excluding the 2018 and 2019 samples. The results show that all conclusions remain unchanged, proving that the conclusions of this study are robust.[2]

6 Further Analysis

The introduction of text analysis methods opens up more possibilities for empirical research in strategic management. However, traditional variable construction is based on the bag of words method relies on researchers' pre-established keywords, which lack transparency

[2] Due to space constraints, the empirical results of the robustness tests are not displayed in the text. Please contact the authors for further details if needed.

and interpretability (Rule et al., 2015). Even if the keywords are clearly defined, researchers cannot fully understand the intentions behind strategic decision-makers mentioning those keywords. For example, biometrics technology is generally considered part of a manufacturing enterprise's product R&D strategy, but it often appears alongside keywords like "internet finance," "third-party payment," and "credit rating," indicating a concentration on digital finance strategy.

Referencing the research of sociologists such as Nambisan et al. (2017), this study introduces text network analysis to analyze the 4,166 annual reports in the research sample. A digital strategy keyword network is constructed, and community identification is performed using the Louvain method to deconstruct the digital strategy. Unlike a predefined bag of words, digital strategy-related keywords based on different underlying digital technologies present cluster results at the strategic level. With reference to the research on digital innovation by Liu et al. (2020), the digital strategy is classified into digital finance strategy, digital marketing strategy, and digital product and manufacturing strategy based on community identification results (resolution = 1.0), as shown in Table 4.

Table 4 Digital Strategy Categories Based on Text Network Analysis

Variable	Definition	Constituent keywords
DIG_FIN	Digital finance strategy	Internet finance, third-party payment, facial recognition, big data, biometrics technology, credit rating, blockchain, smart data analysis, identity verification, open banking, fintech, and digital currency
DIG_MKT	Digital marketing strategy	E-commerce, B2B, O2O, C2C, C2B, B2C, smart marketing, smart customer service, and mixed reality
DIG_PRO	Digital product and manufacturing strategy	Smart transportation, IoT, smart home, wearable technology, smart agriculture, virtual reality, smart tourism, augmented reality, networking, autonomous driving, deep learning, cloud computing, neuromorphic computing, in-memory computing, distributed computing, cognitive computing, green computing, virtual reality, billion-level concurrency, natural language processing, intelligent robots, facial recognition, mobile internet, business intelligence, heterogeneous data, data visualization, AI, big data, integrated architecture, voice recognition, machine learning, and cyber-physical systems

The specific steps to construct the digital strategy keyword network are as follows. First, we utilize the Chinese word segmentation package jiaba (in Python) to segment the annual reports into words, count the frequency of each digital strategy-related keyword in every annual report, and construct a bipartite network of digital strategy-related keywords and annual reports to represent the frequency distribution of digital strategy-related keywords in the annual reports. Second, we convert the bipartite network of digital strategy-related keywords and annual reports into a unipartite network of digital strategy-related keywords. This keyword co-occurrence matrix ($\boldsymbol{M}$) represents the network of co-occurrence relationships between digital strategy-related keywords. $m_{i,j}$ in the matrix at row i and column j indicates the strength of the relationship between keyword i and

keyword j (Bouncken & Barwinski, 2020). For example, if keyword A appears N_{Aa} times in annual report a and keyword B appears N_{Ba} times in the same report, then annual report a contributes a relationship strength of $N_{Aa}N_{Ba}$ to the relationship between keywords A and B. Given N annual reports in the sample and the frequency of keyword w in annual report n is N_{wn}, $m_{i,j}$ can be represented as:

$$m_{i,j} = \sum_{n=1}^{N} N_{in} N_{jn}. \tag{9}$$

The effect of different digital strategies on the main hypothesis is further examined, and Table 5 presents the results with the dependent variable being digital technological innovation. The coefficients for digital finance strategy and digital marketing strategy are not significant ($\beta = 0.104$, $p > 0.1$; $\beta = -0.176$, $p > 0.1$). However, the coefficient for digital product and manufacturing strategy is positive and significant ($\beta = 0.2$, $p < 0.01$). Green technology innovation mainly refers to technologies, processes, and products that reduce environmental pollution and the use of raw materials as well as utilize green energy. For manufacturing enterprises, financial and marketing strategies typically do not directly relate to their core product technologies and production processes. Hence, they have no direct substantial effect on green technology innovation. Table 6, which presents the effect of digital product and manufacturing strategy and digital resource investment on green technology innovation, shows that digital resource investment continues to play a significant mediating role between digital product and manufacturing strategy and green technology innovation. This further validates the hypothesis that digital strategy guides enterprises to digitalize products, implements smart production processes, and increases digital resource investment, thereby promoting green technology innovation.

Table 5 The Effect of Heterogeneous Digital Strategy on Green Technology Innovation

Variable	(1)	(2)	(3)
	GREEN_INN	*GREEN_INN*	*GREEN_INN*
DIG_MKT	0.104 (0.198)		
DIG_FIN		–0.176 (0.176)	
DIG_PRO			0.200*** (0.000)
Constant	–21.515*** (0.000)	–21.454*** (0.000)	–20.480*** (0.000)
Observations	4,154	4,154	4,154
Industry fixed effect	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes
R^2	0.109	0.109	0.112

Note. *** $p < 0.01$.

Table 6 The Effect of Heterogeneous Digital Strategy on Green Technology Innovation

Variable	(1)	(2)	(3)	(4)
	GREEN_INN	*DIG_INV*	*GREEN_INN*	*GREEN_INN*
DIG_PRO	0.200*** (0.000)	0.014*** (0.000)		0.193*** (0.000)
DIG_INV			0.538* (0.051)	0.431 (0.120)
Constant	–20.480*** (0.000)	1.477*** (0.000)	–22.180*** (0.000)	–21.046*** (0.000)
Observations	4,154	4,154	4,166	4,154
Industry fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
R^2	0.112	0.183	0.110	0.112

Note. *** $p < 0.01$ and * $p < 0.1$.

7 Conclusions

In the era of dual strategic implementation of industrial digital transformation and the goals of carbon peaking and carbon neutrality, this study focuses on the intersection of corporate digitalization and green transformation, a hot topic in interdisciplinary research. From the perspectives of strategic management, the RBV, and the IBV, it systematically explores the relationship and mechanisms between digital transformation and green technology innovation capability of enterprises, as well as the heterogeneous effect of ownership structure. It is expected to provide empirical evidence for the relationship between digital transformation and green development. Theoretically, this study elucidates how digital transformation promotes green technology innovation and examines the heterogeneous effect of ownership structure from the dual perspectives of resource and strategy. This offers important theoretical insights into the mechanisms and heterogeneous factors affecting the effect of digital transformation on green technology innovation. It provides empirical evidence for the deeper application and refinement of strategic management, the RBV, and the IBV in the digital era. In terms of the policy implications, the findings reveal the significance of digital transformation for green development from the perspective of strategic management (Cai, 2021). This offers scientific decision-making insights for central and local governments to further refine policies related to digital transformation, carbon peaking, and carbon neutrality, and to integrate the digital economy and green development policies. This, in turn, can further incentivize enterprises to seize opportunities for industrial digitalization and accelerate the synergistic transformation of digital and green practices.

While this study provides theoretical and empirical insights into the relationship, mechanisms, and contextual factors of digital transformation and green technology innovation among enterprises, there are certain limitations due to data availability and the focus of the study that need to be addressed in future research. First, due to the limitations of publicly disclosed company data, this study could not further distinguish between different

stages and attributes of digital resource investment. Future research should employ large-scale surveys and other methods to explore this in depth. Second, digital transformation and green technology innovation require substantial resource investment, which may face financing constraints. Beyond ownership structure, future research should examine the heterogeneous effect of financing constraints and other fintech factors on this process. Third, the specific strategies, investment intensity, and effectiveness of green transformation in digital transformation can vary across different industries and regions. Future research should investigate the effect of external contextual factors, such as the level of digital economy development in different industries and regions.

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