sustainability

MDPI

Article

Can Digital Transformation Promote Green Technology Innovation?

Long Xue, Qianyu Zhang, Xuemang Zhang * and Chengyu Li *

School of Economics and Management, Zhengzhou University of Light Industry, Science Avenue 136, Zhengzhou 450002, China; xl2017018@sina.com (L.X.); zqy220420@163.com (Q.Z.)
* Correspondence: xuemang_z@163.com (X.Z.); chengyu.li@zzuli.edu.cn (C.L.)

Abstract: Using the index of the degree of digital transformation of enterprises constructed based on text analysis, and combining the data of Shanghai and Shenzhen A-share listed companies from 2007 to 2020, a panel data model was established to empirically study the impact of digital transformation on green technology innovation and the mechanism of action and to further analyze the impact of heterogeneity. The results show that digital transformation can significantly promote green technology innovation, and its internal mechanism is that digital transformation can improve the level of green technology innovation by alleviating financing constraints and attracting government subsidies. Compared with nonstate-owned enterprises and small and medium-sized enterprises, digital transformation plays a more significant role in promoting green technology innovation in state-owned enterprises and large-scale enterprises. Therefore, the government should regulate the market order and formulate reasonable financial policies to provide policy and financial support for enterprises to carry out digital transformation, mobilize the willingness of enterprises to carry out green technology innovation and improve the level of green technology innovation in China.

Keywords: digital transformation; green technology innovation; financing constraints; government subsidies; green development

check for updates

Citation: Xue, L.; Zhang, Q.; Zhang, X.; Li, C. Can Digital Transformation Promote Green Technology Innovation? *Sustainability* **2022**, *14*, 7497. https://doi.org/10.3390/su14127497

Academic Editor: Luigi Aldieri

Received: 29 May 2022
Accepted: 16 June 2022
Published: 20 June 2022

1. Introduction

In the post-epidemic period, the green recovery plan with carbon neutrality as the core has become the world's largest consensus [1]. In 2021, The State Council of the People's Republic of China issued the "Carbon Peaking Action Plan before 2030", which listed green and low-carbon technological innovation actions as the "Top Ten Carbon Peaks", encouraging all industries to carry out green reform, development and innovation. [2] In addition, under the call of the new development concepts of "building a market-oriented green technology innovation system" and "innovation, coordination, green, openness, and sharing", green technology innovation reflects the two development concepts of green development and innovation-driven development. The combination point is to jump out of the vicious circle of "economic development–environmental pollution" and pursue a "win–win" development model for the environment and economy. Green technology innovation is the first driving force for green development and an important focus for promoting the construction of an ecological civilization. As the main initiators, demanders and implementers of innovation, enterprises should shoulder the burden of sustainable development, i.e., the responsibility of accelerating green technology innovation and promoting the economy and environment.

In the "14th Five-Year Plan" and the 2035 long-term vision target outline, "Accelerating digital development and building a digital China" is listed as a separate article, the article proposes that we should take the digital transformation as the driving force of the changes in production, life and governance; vigorously promote the deep integration of the digital economy and the real economy [3]; and encourage the promotion of digital transformation to enable all walks of life transformation and upgrading so as to provide new directions and new paths for the innovative development of enterprises. Digitalization is a transformation, not a technical challenge, and it has a lasting impact on businesses. Organizations that cultivate digital technology and strategic thinking will be in an advantageous position in market competition. Data technologies such as artificial intelligence, the cloud computing technology, and big data analysis affect enterprises' innovative business practices in terms of green manufacturing, waste manufacturing, and efficient manufacturing, forcing enterprises to innovate green technologies and maximize the use of resources to reduce the possibility of environmental pollution [4]. However, at this stage, enterprises have insufficient understanding of the importance and connection of digital transformation and green technology innovation. The supporting role of digital transformation on green technology innovation has not been fully exerted, and green technology innovation still faces serious financing bottlenecks. Based on this, this paper mainly answers the following questions: (1) Does digital transformation have a significant positive role in promoting green technology innovation? (2) By what mechanism is this effect achieved? (3) Is the impact heterogeneous in terms of property rights and firm size? This paper takes the data of Shanghai and Shenzhen A-share listed companies from 2007 to 2020 as a sample, establishes a panel data model, empirically studies the relationship between digital transformation and green technology innovation, and tests the transmission mechanism of digital transformation to promote the improvement of green technology innovation. This not only helps to accurately reveal the direct impact of digital transformation on green technology innovation and the intermediary transmission effect and fills the relevant research gaps but also is of great significance for improving the level of corporate green technology innovation and promoting green economic growth and achieving the double carbon goal in China.

The structure of this paper is as follows. In Section 2, the literature related to, digital transformation and green technology innovation is reviewed, and the gaps in the existing literature and the marginal contributions of this study are presented. In Section 3, the theoretical analysis and hypotheses are presented for the questions raised in the introduction. In Section 4, the empirical model is designed, and the variables in the model are explained in detail. In Section 5, benchmark regression analysis and mechanism analysis are carried out, the experimental results are discussed in depth, and questions (1) and (2) are answered, respectively. In Section 6, robustness tests are conducted to enhance the robustness of the findings by replacing the explanatory variables, endogeneity tests and lagged effects tests. In Section 7, heterogeneity analysis is conducted to study the heterogeneity effect of digital transformation on green technology innovation in different property rights and enterprise size, answering question (3). In Section 8, this paper summarizes and puts forward relevant policy suggestions.

2. Literature Review

2.1. Research on the Digital Transformation of Enterprises

Digitalization is becoming the main driver for enterprises to carry out transformation and innovation. The deep integration of digital technology and business process will help enterprises upgrade and transform existing technology, products and business process by using new business model and help enterprises improve their market competitiveness [5,6].

Most current research by scholars focuses on the influencing factors of digital transformation and its economic consequences. Regarding the influencing factors of digital transformation, Matarazzo et al. argue that perception and learning capabilities are the first drivers of digital transformation, and the improvement of these dynamic capabilities will help companies maximize the value of digital transformation [7]. Li argues that entrepreneurs can drive digital transformation by managing cognitive renewal, managing social capital development, business team building, and organizational capacity building [8]. Li et al. believed that organizational mindfulness will lead companies to develop strategies about digital transformation to avoid digital technology rigidity and thus maximize the value of digital technology [9]. Regarding the economic consequences of digital transformation, Borowski found that the digitalization of energy companies can help them reduce operational costs and increase productivity as well as improve the safety, efficiency, and durability of their energy systems, further increasing the speed of development and rapid adaptation to market demand [10]. Based on the research of real enterprises, He and Liu found that digital transformation can effectively reduce costs and improve the utilization rate of assets, thus promoting the improvement of economic benefits [11]. However, Hajli et al. found that only a small percentage of enterprises could benefit from digital transformation [12]. Qi and Cai concluded that the increased cost of introducing digital technology would increase with the continuous iteration of digital technology, making it impossible to measure the total impact of digital transformation on enterprises [13].

2.2. Research on Corporate Green Technology Innovation

Green technology innovation is the primary driving force to lead the green development of enterprises and provide important support for high-quality economic development; overall, it is an important idea to lead the new technological revolution in the new situation. Green technology innovation can effectively help enterprises to realize the value of symbiosis of ecological performance and economic performance, and finally make the resource allocation reach the optimal state. Thus, the study of the influencing factors of enterprise green technology innovation has become a hot topic nowadays.

From the macro level, most scholars study the impact of environmental regulation on green technology innovation. For example, Porter and Linde argue that environmental regulation will produce an "innovation compensation" effect, which will force firms to engage in green technology innovation [14], i.e., the "Porter hypothesis" which is confirmed by a large number of scholars through empirical studies [15,16]. To address this, scholars have classified environmental regulations and analyzed the degree of incentive of different types of environmental regulations on green technology innovation. Luo et al. found through empirical evidence that command-and-control and informal regulations significantly promoted green technology innovation in China, supporting Porter's hypothesis [17]. Yi et al. argued that command-based policy instruments could only be implemented when the intensity of implementation reached a certain threshold or when the intensity of implementation of market-based policy instruments was controlled to a certain level [18]. In addition, some scholars have carried out studies on the influencing factors of green technology innovation from other macro-environmental perspectives. Lv et al. studied the influence of financial structure, scale, and efficiency on green technology innovation from the perspective of China's financial market environment, and the results show that a reasonable financial structure will promote the development of green technology innovation [19]. Tang et al. found that the construction of telecom infrastructure will improve the informatization level of enterprises, increase the progress space and propagation speed of green technology, and thus have an incentive effect on green technology innovation [20]. From the micro level, scholars mainly analyze and discuss from the internal characteristics of enterprises, Palčič and Prester argue that advanced manufacturing technology contributes to both company performance and green innovation [21]. Ma et al. found that executive characteristics have a positive impact on green technology innovation from the perspective of corporate governance, and when the whole team maintains a moderate fault line strength, it will lead to endogenous innovation dynamics from the top down [22].

2.3. Research on Digital Transformation and Enterprise Green Technology Innovation

There is little literature linking digital transformation with green technology innovation, and there is a wide divergence of views in the existing literature on the issue of concern in this paper. One view holds that digital transformation will significantly promote green technology innovation. Through empirical research, Wang et al. found that the improvement of digitization level will effectively enhance the technology integration ability of enterprises, thus promoting the green technology innovation activities of resource-based enterprises [23]; Song et al., taking heavily polluting enterprises as the sample, found that enterprise digitization mainly promoted enterprise green technology innovation by improving the enterprise information-sharing level and knowledge integration ability [24]. Li and Shen found that digital transformation significantly promoted green innovation, and its promotion effect was more obvious in enterprises with poor quality of internal control and low shareholding of institutional investors [25]. The other holds that digital transformation does not significantly promote green technology innovation. Ghasemaghaei and Calic found that while data diversity and speed improved firms' innovation performance, data volume did not play a key role in improving firms' innovation performance; i.e., big data are not always good data [26].

Existing studies provide useful references for this paper, but the following areas worth further research can be found in the existing literature. First, although some scholars have studied the impact of digital transformation on enterprise green technology innovation, they mostly choose heavy polluting enterprises or resource-based enterprises as research samples, while digital transformation is the current trend of enterprise development, and its impact on enterprise green technology innovation leads to inevitably biased conclusions if it is only limited to specific types of enterprises for research. Secondly, in existing studies, scholars have mostly explored the mechanism of digital transformation affecting green technology innovation from the improvement of technological capability brought by digital transformation, but less attention has been paid to the convenience brought by digital transformation in helping enterprises finance and attract government subsidies, which in turn affects the mechanism of green technology innovation of enterprises. Finally, scholars in existing studies have not paid attention to the heterogeneous effects of digital transformation affecting enterprise green technology innovation across different property rights nature and enterprises of different sizes.

Therefore, this paper selects all the listed companies in Shanghai and Shenzhen A-shares as the research sample and constructs a panel data model to study the impact of digital transformation on green technology innovation. Furthermore, considering that green technology innovation cannot be achieved without sufficient financial support, this paper explores the mechanism of digital transformation affecting enterprise green technology innovation through two channels: digital transformation affecting enterprise financing constraints and government subsidies. On this basis, we further analyze the heterogeneity of the impact of digital transformation on green technology innovation among enterprises with different property rights and different sizes. Compared with existing studies, the marginal contributions of this paper may lie in: (1) the study sample is selected more comprehensively, avoiding the possible research bias brought by selecting enterprises in a particular industry as a sample for the study; (2) exploring the role mechanism of digital transformation affecting enterprise green technology innovation from the perspective of financing constraints and government subsidies provides a new research idea to explore the role mechanism of digital transformation affecting enterprise green technology innovation; and (3) researching the heterogeneity effect of digital transformation affecting enterprise green technology innovation for different property rights nature and different enterprise scales, which makes up for the deficiency in existing studies.

3. Theoretical Analysis and Research Hypothesis

3.1. Digital Transformation and Green Technology Innovation

With the advent of the era of the digital economy, digital transformation has become an irreversible trend. While effectively promoting resource sharing and resource optimization, it also meets the data element requirements of green technology innovation and penetrates all aspects of green technology innovation to promote the improvement of the level of green technology innovation.

With the help of digital technology, information knowledge will be generated, shared and exchanged in the innovation network with the characteristics of low cost and rapid dissemination in real time. In the preparation stage, the use of data technology helps enterprises reintegrate and plan information such as products, processes, resources, and the external environment, effectively solve the problems of information departmentalization, fragmentation, and information asymmetry, and form a complete data information system to help enterprises make scientific decisions that are conducive to the common development of economic benefits and environmental protection. At the same time, enterprises use advanced digital technology to identify and obtain more network resources, break the information island, grasp the market development trend and consumer demand, and accelerate the formation of green creative ideas while forming their resource network [27].

In the development stage, modern enterprises can use internet technology to establish or participate in the low-cost cooperation and exchange platforms of relevant virtual green technology innovation organizations, thereby breaking the learning barriers between organizations that reduce knowledge and information resources due to economic, geographical and time constraints. This helps the enterprises identify, acquire and absorb costs; realize collaborative innovation, resource sharing and win–win cooperation among organizations; and accelerate the progress of research and development and the innovation of green technology.

In the production process, with green as the guide, data management as the core, and technology as the key element, the digital management of the entire life cycle of product-related production factors, production data, and production processes are realized, and the enterprise product development and production process are supported. This helps the enterprises adjust the holdings of production factors in real time, optimize resource allocation, realize lean production, save energy and reduce emissions, avoid resource waste, improve production efficiency, identify redundant resources and provide resource guarantees for green technology innovation.

In the consumption link, big data technology is used to sort out and integrate information such as customer value, satisfaction, and the repurchase possibility of consumers and analyze customers' consumption needs and product supply trends in detail to provide a clear direction for green technology innovation. This helps the enterprises achieve effective matching between supply and demand and intelligent monitoring and precise marketing of business operations, optimize resource allocation, reduce production costs, enhance production capacity, and provide an impetus for green technology innovation.

Based on the above analysis, this paper believes that digital transformation penetrates all aspects of green technology innovation, thus effectively promoting green technology innovation. Therefore, this paper proposes Hypothesis 1.

H1. *Digital transformation has a significant role in promoting the improvement of enterprises' green technology innovation level*.

3.2. Analysis of Influence Mechanism of Financing Constraint Channels

The management is the main initiator of green technology innovation, and the R&D team is the important driving force of innovation. Sufficient R&D investment will help knowledge workers give full play to their value and output innovation achievements smoothly [28,29]. The financing constraint of enterprises makes the R&D investment insufficient to a large extent, which affects the innovation output [30]. Since the green technology innovation industry has the characteristics of high risk and high income, in the early stage of research and development, the investment object has not yet formed the expected income of the entity, and the investment risk is extremely high. The investment return period is long, which makes it difficult to obtain a steady stream of high-quality capital inflows [31] compared to other industries and contributes to more serious financing constraints. The investment and financing selection process of an enterprise is a process in which various stakeholders play games to maximize their interests. At different stages of enterprise development, enterprises' demand for capital will change accordingly. The moral hazard caused by information asymmetry makes investors cautious about enterprises' credit behavior, which leads to financing constraints. Digital transformation enables enterprises to take advantage of digital technology to reduce information asymmetry and principal–agent costs in the credit market, thereby alleviating financing constraints and raising sufficient funds for enterprises to carry out green technology innovation activities.

First, digital transformation alleviates the problem of information asymmetry to a certain extent. For enterprises, a sound digital foundation and digital industry will increase the internal and external information communication channels of the enterprise, amplify the speed, breadth and transparency of information dissemination, and help financial institutions grasp the financial and non-financial information of the capital demander more quickly. For investment institutions, pre-investment institutions can evaluate and integrate enterprise information in an all-around way, promote the rapid matching of information on both sides, improve the efficiency of enterprises in obtaining financial assistance, alleviate the problem of credit mismatch, and supervise the use and allocation of funds within the enterprise in real-time information, such as capital flow, expected income, repayment probability, etc., to effectively avoid green innovation risks caused by irregular market operations and unbalanced internal control of enterprises. This optimizes the resource allocation and risk prevention and control system of investment institutions, reducing credit risks such as bad debt losses, improving investor confidence and willingness, further breaking the shackles of financing constraints, and providing sufficient capital guarantees for the green technology innovation of enterprises [32].

Second, digital transformation has reduced principal–agent costs to a certain extent. The extensive application of digital technology further reduces the cost of information acquisition by investment institutions and the execution cost of the supervision and control of the subsequent use of funds and enhances the efficiency of supervision and repayment management of enterprises. The effective combination of green technology innovation activities provides more opportunities for green technology innovation activities.

Third, digital transformation improves the environment for the external information dissemination of enterprises and helps enterprises broaden financing channels. The development and application of digital technology help enterprises integrate financial resources that are small and scattered in the market. Compared with the difficulty of traditional transaction costs that are too high and difficult-to-absorb funds, technologies such as big data, artificial intelligence and blockchain help enterprises achieve low cost. They collect massive amounts of data in a risky and high-reward manner and absorb and integrate more funds for enterprises to carry out green technology innovation activities [33].

Based on the above analysis, we find that digital transformation can effectively alleviate the difficulties of corporate financing constraints so that enterprises can obtain financial support in a timely, accurate and sufficient manner to carry out green technology innovation activities. Therefore, Hypothesis 2 is proposed.

H2. *Digital transformation promotes green technology innovation by easing financing constraints*.

3.3. Analysis of Influence Mechanism of Government Subsidy Channels

Difficulty in financing is the main factor hindering green technology innovation. In addition to financing from social capital, government subsidies are the most direct external resource support for enterprise R&D and innovation. Innovation is "icing on the cake" [34]. Currently, digital transformation has become a general trend. The requirements of the times, policies and regulations have created a good environment for encouraging enterprises to carry out digital transformation. Enterprises that actively comply with social trends and actively respond to the call of the times are more likely to be favored by the government; the dynamic capabilities contained in it can significantly change the organization mode, information structure, production mode, etc., of the enterprise and ultimately affect the innovation consciousness and behavior of the enterprise, help the enterprise form its core competitiveness, and realize the final strategic adjustment [35] and business potential. Compared with traditional enterprises, such enterprises are more likely to attract government subsidies. Finally, digital transformation helps enterprises effectively integrate resources, technologies, and talent so that funds flow to places with higher utilization efficiency, thereby improving the problem of resource misallocation. At the same time, according to the big data tracking user needs, digital transformation achieves precise production, thereby optimizing the structure of capital utilization, improving the efficiency of capital utilization, and maximizing the role of government subsidies in promoting green technology innovation activities, thereby attracting more government subsidies. Therefore, Hypothesis 3 is proposed.

H3. *Digital transformation promotes green technology innovation by attracting government grants.*

4. Study Design

4.1. Sample Selection and Data Sources

This paper takes Shanghai and Shenzhen A-share companies from 2007 to 2020 as a sample and performs the following initial processing: ① ST and *ST company samples are excluded. ② Companies with missing data and abnormal data are excluded. ③ Financial companies are excluded. To prevent extreme values from affecting the results, the continuous variables at the enterprise level are abbreviated at the 1% level. After the above processing, 15,029 groups of observations are finally obtained. Among them, the green patent data come from the Chinese Research Data Services Platform (CNRDS), and the financial data of other companies are downloaded from the China Stock Market Accounting Research Database (CSMAR).

4.2. Definition of Main Variables

4.2.1. Explained Variable

Green technology innovation (LNPATENT). The number of patent applications is often used to measure the innovation output of enterprises in the literature. Green patents refer to inventions, utility models and design patents with green technology as the theme of the invention. Among them, invention patents can better reflect the technological innovation of enterprises, which is followed by utility models and designs. This paper draws on the variable selection method of Li and Zheng, obtains relevant data from the Chinese Research Data Services Platform (CNRDS), and takes the natural logarithm of the number of invention patents plus 1 as an indicator to measure the company's green technology innovation [36].

4.2.2. Explanatory Variable

Degree of digital transformation (LNDC). Digitization mainly refers to the wide application of digital technologies, including artificial intelligence technology, blockchain technology, cloud computing technology, big data technology, and digital technology applications. This paper draws on the research of Wu et al. and uses the text mining method to calculate the frequency of subdivision indicators of related technologies appearing in the report, adds them to the sum and adds 1 to take the natural logarithm as a measure of the degree of digital transformation of enterprises. All data come from the China Stock Market Accounting Research Database (CSMAR) [37].

4.2.3. Mediating Variables

Financing constraint (SA). This paper draws on the research of Hadlock and Pierce and uses the absolute value of the SA index to measure financing constraints [38].

Government grants (LNZFBZ). The data come from the government subsidy part of other income in the annual report of the sample listed companies.

4.2.4. Control Variables

Referring to the relevant literature, this paper selects the age of business (LNAGE), the cash flow (CASH), the shareholding ratio of the top ten shareholders (TOP10), the ratio of fixed assets (FAT), the growth of the company (GROWTH), the current ratio (LIQUID), and the asset–liability ratio (LEV) as holding variables. Industry (IND) and year (YEAR) dummy variables are set to control the effects of industry and time on the regression results.

The specific definitions of the key variables, mediating variables and control variables in this paper are listed in Table 1.

Table 1. Variable Definitions.

Variable Type	Name	Symbol	Definition
Explained variable	Green technology innovation	LNPATENT	Applications for green inventions in that year to take the natural logarithm
Explanatory variable	Degree of digital transformation	LNDC	Frequency of occurrence of subdivision indicators of artificial intelligence technology, blockchain technology, cloud computing technology, big data technology, and digital technology application in the report is summed up and added to 1 to take the natural logarithm
Mediating variables	Financing constraints	SA	$\lvert SA \rvert = \lvert -0.737 \times Size + 0.043 \times Size2 - 0.040 \times Age \rvert$
	Government subsidy	LNZFBZ	Other income parts of the announcement
Control variables	Business age	LNAGE	Add 1 to the difference between the date of establishment of the company and the year of the current year and then take the logarithm
	Cash flow	CASH	Monetary fund/total assets
	Shareholding ratio of the top ten shareholders	TOP10	Sum of shareholding ratios of the top ten shareholders
	Fixed asset ratio	FAT	Net fixed assets/total assets
	Business growth	GROWTH	(This year's operating income − last year's operating income)/last year's operating income)
	Current ratio	LIQUID	Current assets/current liabilities
	Asset–liability ratio	LEV	Total liabilities/total assets
	Industry	IND	Industry dummy variable
	Year	YEAR	Annual dummy variable

4.3. Empirical Model Design

To effectively identify the relationship between enterprise digital transformation and green technology innovation, this paper sets the following benchmark regression shown in Model (1):

$$LNPATENT_{i,t} = \alpha_0 + \alpha_1 \mathrm{LNDC}_{\mathrm{i,t}} + \alpha_2 \mathrm{Con}_{\mathrm{i,t}} + \sum \mathrm{YEAR} + \sum \mathrm{IND} + \varepsilon_{\mathrm{i,t}} \tag{1}$$

LNPATENT represents green technology innovation, LNDC represents the degree of digital transformation, Con represents the remaining control variables, YEAR and IND are annual and industry dummy variables used to control time and industry effects, and ε represents random disturbance terms.

To verify H2 and H3, this paper introduces the intersection term of digital transformation and financing constraint or government subsidy based on Model (1), and it builds Model (2):

$$\begin{gathered} LNPATENT_{i,t} = \beta_0 + \beta_1 LNDC_{i,t} + \beta_2 SA_{i.t}/LNZFBZ_{i,t} + \beta_3 LNDC_{i,t} \times SA_{i,t}/LNZFBZ_{i.t} \\ +\beta_4 Con_{i,t} \ + \sum IND + \sum YEAR + \varepsilon_{i,t} \end{gathered} \tag{2}$$

SA stands for financing constraints, *LNZFBZ* stands for government subsidies, and the meanings of the remaining variables are consistent with Model (1). If the coefficient β_3 is significant and greater than zero, it means that the two mechanisms of financing constraints and government subsidies are established.

5. Empirical Results and Analysis

5.1. Descriptive Statistics

In Table 2, the average value of the digital transformation degree (LNDC) is 1.775, indicating that domestic listed companies have a low degree of digital transformation and weak awareness of transformation; the minimum and maximum values of green technology innovation (LNPATENT) are 0 and 4.304, respectively, with a standard deviation of 1.011, indicating that the level of technological innovation varies greatly among enterprises; the value distribution of other control variables is consistent with the actual situation, and no abnormality has been found.

Table 2. Descriptive Statistical Analysis.

Variable	Sample	Mean	Median	SD	Min	Max
LNPATENT	15,029	0.681	0.000	1.011	0.000	4.304
LNDC	15,029	1.775	1.609	1.337	0.000	4.997
LNAGE	15,029	2.849	2.890	0.358	0.693	4.143
CASH	15,029	0.203	0.162	0.142	0.022	0.696
TOP10	15,029	0.595	0.607	0.148	0.243	0.902
FAT	15,029	0.180	0.146	0.143	0.002	0.655
GROWTH	15,029	0.385	0.173	0.789	−0.608	5.114
LIQUID	15,029	2.688	1.787	2.715	0.385	17.52
LEV	15,029	0.403	0.393	0.199	0.051	0.861

5.2. Benchmark Regression Results

Table 3 reports the benchmark regression results of the degree of digital transformation of enterprises on green technology innovation. In the regression model, when we control the industry, annual dummy variables and control variables, the regression coefficients of digital transformation are 0.1172, 0.1266, 0.1203, and 0.1149, respectively, and each is significant at the 1% level. This result confirms the establishment of H1 and answers question (1), which shows that enterprise digital transformation has a significant promoting effect on green technology innovation. Specifically, digital transformation enables enterprises to reorganize innovative elements such as product manufacturing, design and development, and technological processes with representative digital technologies, innovate green energy-saving technologies, improve product added value and market competitiveness, and promote the improvement of enterprises' green technology innovation level.

Table 3. Benchmark regression results.

Variable	(1)	(2)	(3)	(4)
	LNPATENT			
LNDC	0.1172 ***	0.1266 ***	0.1203 ***	0.1149 ***
	(19.22)	(18.35)	(19.16)	(16.93)
LNAGE			0.0070	0.0629 **
			(0.30)	(2.55)
CASH			0.0180	0.2769 ***
			(0.26)	(4.14)
TOP10			−0.1089 *	0.0143
			(−1.96)	(0.26)
FAT			−0.3173 ***	−0.3720 ***
			(−5.06)	(−5.38)
GROWTH			−0.0110	−0.0075
			(−1.07)	(−0.75)
LIQUID			−0.0042	−0.0117 ***
			(−0.99)	(−2.93)
LEV			1.0797 ***	1.1931 ***

Table 3. *Cont.*

Variable	(1)	(2)	(3)	(4)
	LNPATENT			
			(19.98)	(22.07)
CONS	0.4729 ***	0.1527	0.1463 *	−0.4525 ***
	(34.90)	(1.02)	(1.67)	(−2.74)
IND	No	Yes	No	Yes
YEAR	No	Yes	No	Yes
N	15,029	15,029	15,029	15,029
R^2	0.0240	0.1766	0.0728	0.2250
Adj−R^2	0.0239	0.1716	0.0723	0.2199
F	369.4899	35.2103	147.3944	44.2372

The number in parentheses in the table is t-statistic; *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

5.3. Examination of Impact Mechanism of Digital Transformation on Green Technology Innovation

This paper examines the effect mechanism of digital transformation on green technology innovation from the perspectives of financing constraints and government subsidies. Table 4 mainly reports the test results of the mechanism of financing constraints and government subsidies in the impact of digital transformation on green technology innovation. Column (1) shows that the multiplication term of digital transformation and financing constraints (LNDC × SA) is positively significant at the 1% level, and the coefficient is 0.1283. The results indicate that financing constraint is a functional channel in the process of digital transformation, promoting green technology innovation. The above results verify H2 and answer question (2): digital transformation can improve the level of green technology innovation by alleviating financing constraints. That is, digital transformation has injected new vitality into enterprises, enabling enterprises to effectively integrate the internal information and resources of enterprises by using artificial intelligence, cloud computing, big data and other technologies and rationally improve information with external investment institutions by strengthening digital governance capabilities and improving information transparency. This helps to reduce information asymmetry and unbalanced supply and demand, which improves their willingness to lend, greatly alleviates the problem of the external financing constraints of enterprises, attracts a large number of funds for enterprises, and increases sufficient financial power for green technology innovation.

Column (2) shows that the multiplication term of digital transformation and government subsidies (LNDC × LNZFBZ) is positively significant at the 1% level with a coefficient of 0.0352. The results show that government subsidy is a functional channel in the process of digital transformation to promote green technology innovation. The above results verify H3 and answer question (2): digital transformation promotes green technology innovation by attracting government subsidies. That is, the digital transformation of the enterprise actively responds to the call of the times and the government, and through the reconstruction and optimization of the enterprise's organizational structure, marketing mode, and production mode, it improves its operation and management efficiency and releases the signal of the enterprise's strong productivity. The disclosed information is screened, and it attracts the government to provide free funds for enterprises for innovation activities and lays a certain capital foundation for enterprises to carry out green technology innovation.

Table 4. Test results of mechanism of financing constraints and government subsidy channels.

Variable	(1)	(2)
	LNPATENT	
LNDC	0.1157 ***	0.0767 ***
	(17.01)	(8.41)
SA	−0.6875 ***	
	(−13.40)	
LNDC × SA	0.1283 ***	
	(5.71)	
LNZFBZ		0.2745 ***
		(38.26)
LNDC × LNZFBZ		0.0352 ***
		(7.24)
LNAGE	0.4420 ***	0.0532
	(11.89)	(1.47)
CASH	0.2933 ***	0.2204 **
	(4.39)	(2.37)
TOP10	−0.1023 *	−0.1084
	(−1.88)	(−1.49)
FAT	−0.3611 ***	−0.4525 ***
	(−5.20)	(−4.68)
GROWTH	−0.0070	0.0082
	(−0.70)	(0.60)
LIQUID	−0.0168 ***	0.0001
	(−4.19)	(0.02)
LEV	1.1469 ***	0.7181 ***
	(21.00)	(9.13)
CONS	1.1280 ***	−4.3333 ***
	(5.49)	(−18.96)
IND	Yes	Yes
YEAR	Yes	Yes
N	13,523	7887
R^2	0.3139	0.3482
Adj−R^2	0.3088	0.3409
F	61.4056	47.3467

The number in parentheses in the table is t-statistic; *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

6. Robustness Analysis

6.1. Test Results after Remeasurement Based on Green Technology Innovation

Table 5 shows the results of the regression of the sum of the number of green inventions and utility models plus 1 to take the natural logarithm as the new explained variable number of patent applications (LNTOTAL). In the regression process, to control the industry, the annual dummy variable and the control variables were selected. The regression coefficients of digital transformation were 0.0976, 0.1247, 0.1086, and 0.1132, and they were all significant at the 1% level. The regression results once again verify the establishment of H1, that is, digital transformation has a positive role in promoting green technology innovation.

Table 5. Robustness test results of remeasure of explained variables.

Variable	(1)	(2)	(3)	(4)
	LNPATENT			
LNDC	0.0976 ***	0.1247 ***	0.1086 ***	0.1132 ***
	(13.38)	(15.63)	(14.52)	(14.50)
LNAGE			−0.0465 *	0.0403
			(−1.68)	(1.42)
CASH			−0.1942 **	0.2362 ***
			(-2.36)	(3.07)
TOP10			−0.1507 **	−0.0173
			(−2.28)	(−0.28)
FAT			−0.2942 ***	−0.2661 ***
			(−3.94)	(−3.35)
GROWTH			−0.0238 *	−0.0089
			(−1.94)	(−0.77)
LIQUID			−0.0071	−0.0171 ***
			(−1.40)	(−3.70)
LEV			1.3523 ***	1.4810 ***
			(21.01)	(23.82)
CONS	0.7999 ***	0.1261	0.5785 ***	−0.5495 ***
	(49.33)	(0.73)	(5.54)	(−2.90)
IND	No	Yes	No	Yes
YEAR	No	Yes	No	Yes
N	15,029	15,029	15,029	15,029
R^2	0.0118	0.2207	0.0704	0.2754
Adj−R^2	0.0117	0.2159	0.0700	0.2707
F	178.9980	46.4777	142.2887	57.9156

The number in parentheses in the table is t-statistic; *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

6.2. Endogeneity Problem

6.2.1. Propensity Score Matching

Because of the possible problem of sample selection bias, this study used the samples after propensity score matching to perform regression analysis again. ① According to whether the digital transformation (LNDC) has a value, it is recorded as 0 or 1; that is, “1” indicates that the enterprise has undergone digital transformation, and “0” indicates that the enterprise has not undergone digital transformation. ② The propensity score corresponding to each observation sample is calculated by the logit model, in which the explained variables are the digital transformation (LNDC) dummy variables (DCC), and the explanatory variables are all the control variables used in this study. To eliminate the influence of sample selection bias as much as possible, this study uses 1:1 nearest neighbor matching, 1:4 nearest neighbor matching and kernel matching for score matching. ③ The matched samples are used for regression.

Table 6 reports the results of the sample regression analysis after propensity score matching. Column (1) is the result of 1:1 nearest neighbor matching, Column (2) is the result of 1:4 nearest neighbor matching, and Column (3) is the result of kernel matching. The regression results all show that digital transformation and green technology innovation are positively significant at the 1% level, with coefficients of 0.0782, 0.1010, and 0.1150. The regression results again verified the establishment of H1, that is, digital transformation has a significant positive effect on green technology innovation enhancement.

Table 6. Robustness test results for propensity score matching.

Variable	(1) 1:1 Nearest Neighbor Matching	(2) 1:4 Nearest Neighbor Matching	(3) Kernel Matching
		LNPATENT	
LNDC	0.0782 ***	0.1010 ***	0.1150 ***
	(6.81)	(12.23)	(16.92)
LNAGE	−0.0215	0.0124	0.0627 **
	(−0.52)	(0.41)	(2.54)
CASH	0.3049 **	0.3345 ***	0.2762 ***
	(2.52)	(3.83)	(4.12)
TOP10	0.0292	0.0566	0.0143
	(0.32)	(0.85)	(0.26)
FAT	−0.1976 *	−0.3568 ***	−0.3718 ***
	(−1.79)	(−4.37)	(−5.38)
GROWTH	0.0072	−0.0042	−0.0074
	(0.43)	(−0.33)	(−0.74)
LIQUID	−0.0106	−0.0150 ***	−0.0117 ***
	(−1.56)	(−3.17)	(−2.92)
LEV	1.1149 ***	1.1066 ***	1.1937 ***
	(12.44)	(16.74)	(22.07)
CONS	−0.0383	−0.2158	−0.4525 ***
	(−0.16)	(−1.11)	(−2.74)
IND	Yes	Yes	Yes
YEAR	Yes	Yes	Yes
N	4835	9577	15,025
R^2	0.2198	0.2218	0.2249
Adj−R^2	0.2038	0.2138	0.2199
F	13.7550	27.5707	44.2042

The number in parentheses in the table is t-statistic; *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

6.2.2. Heckman Two-Stage Regression Model

To reduce the possible problem of sample selection bias, this study used the Heckman two-stage regression model for testing. In Heckman stage 1, the Probit model was selected for regression, the explained variable is the aforementioned digital transformation dummy variable (DCC), the provincial digital economy development index (SCORE) is used as an exogenous instrument variable, and the annual and industry effects and control variables are controlled. The inverse Mills ratio (IMR) was calculated after the regression. This study draws on the research of Zhao et al. to calculate the provincial digital economy development index from 2011 to 2020 and constructs the entropy weight method from five aspects: internet penetration rate, number of internet-related employees, internet-related output, number of mobile internet users, and digital financial inclusion index [39]. The reason for choosing this variable is that the digital transformation of enterprises is often driven by the policies of the local government and at the same time depends on the support of the local digital infrastructure and development environment. Therefore, the provincial digital economy development index is an important exogenous variable that affects the digital transformation of enterprises.

Table 7 reports the robustness test results of the Heckman two-stage regression. The Probit regression results in the first stage show that the regression coefficient of the provincial digital economy development index is positive, indicating that the rapid development of the provincial digital economy has promoted the digital transformation of local enterprises. In the second-stage regression, the inverse Mills ratio (IMR) was introduced as a control variable into Model (1) and Model (2) for regression. The regression coefficients were 0.1163, 0.1171 and 0.0767, respectively, they were all positively significant at the level of 1% and the results show that all the hypotheses proposed in this paper are valid after considering the endogenous problems caused by sample selection bias.

Table 7. Heckman two-stage robustness test results.

Variable	First Stage	Second Stage		
	DCC	LNPATENT		
LNDC		0.1164 ***	0.1171 ***	0.0762 ***
		(16.60)	(16.74)	(8.40)
SA			−0.6880 ***	
			(−12.85)	
LNDC × SA			0.1576 ***	
			(6.68)	
LNZFBZ				0.2720 ***
				(38.15)
LNDC × LNZFBZ				0.0372 ***
				(7.60)
LNAGE	−0.1167 ***	0.0935 ***	0.4863 ***	0.1319 ***
	(−2.58)	(3.49)	(12.15)	(3.38)
CASH	0.0030	0.2814 ***	0.3007 ***	0.2094 **
	(0.02)	(4.04)	(4.33)	(2.30)
TOP10	0.1829 *	−0.0594	−0.1703 ***	−0.2429 ***
	(1.89)	(−1.04)	(−2.96)	(−3.16)
FAT	−0.9691 ***	−0.1197	−0.0755	0.2473
	(−8.08)	(−1.22)	(−0.77)	(1.43)
GROWTH	−0.0311 *	0.0038	0.0063	0.0292 **
	(−1.72)	(0.36)	(0.60)	(2.06)
LIQUID	−0.0402 ***	−0.0023	−0.0071	0.0253 ***
	(−5.48)	(−0.47)	(−1.43)	(3.19)
LEV	−0.0760	1.2459 ***	1.1828 ***	0.7600 ***
	(−0.78)	(22.05)	(20.78)	(9.79)
SCORE	0.2752 *			
	(1.73)			
IMR		−0.6404 ***	−0.7258 ***	−1.9868 ***
		(−3.54)	(−4.00)	(−4.84)
CONS	1.0847 ***	−0.1427	1.4677 ***	−4.1559 ***
	(4.22)	(−0.91)	(7.35)	(−18.17)
IND	Yes	Yes	Yes	Yes
YEAR	Yes	Yes	Yes	Yes
N	14,254	14,254	14,095	7864
R^2		0.2247	0.2392	0.3478
Adj−R^2		0.2198	0.2342	0.3406
F		45.6137	47.8639	48.2298

The number in parentheses in the table is t-statistic; *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

6.3. Hysteresis Effect

At present, the penetration rate of digital transformation in enterprises is low, and even if a company has undergone digital transformation, its positive impact on enterprises cannot be immediately apparent. That is, the digital transformation of previous years has also had an impact on this year's innovation activities. At the same time, green innovation activities are different from ordinary innovation activities, which require stricter control and planning or even longer periods to produce. Therefore, to avoid the negative impact of time lag on the empirical results, this study uses the number of lag periods for further testing. Table 8 reflects the regression results after lagging digital transformation by one, two, and three periods. The results all show that digital transformation and green technology innovation are positively significant at the 1% level, and their coefficients are 0.1193, 0.1218, and 0.1302. Consistent with the previous conclusions, this result again verifies the validity of H1, that is, digital transformation has a significant role in promoting green technology innovation.

Table 8. Results of lag effect test.

Variable	(1)	(2)	(3)
		LNPATENT	
L1LNDC	0.1193 ***		
	(13.84)		
L2LNDC		0.1218 ***	
		(12.32)	
L3LNDC			0.1302 ***
			(12.01)
LNAGE	0.1122 ***	0.1455 ***	0.1867 ***
	(3.43)	(3.70)	(4.18)
CASH	0.4883 ***	0.6263 ***	0.6564 ***
	(5.46)	(5.93)	(5.60)
TOP10	−0.0012	−0.0183	0.1863 **
	(−0.02)	(−0.22)	(2.09)
FAT	−0.4187 ***	−0.5395 ***	−0.5499 ***
	(−4.64)	(−5.14)	(−4.86)
GROWTH	−0.0004	−0.0074	−0.0056
	(−0.03)	(−0.48)	(−0.33)
LIQUID	−0.0131 **	−0.0206 ***	−0.0263 ***
	(−2.31)	(−2.98)	(−3.34)
LEV	1.2598 ***	1.2418 ***	1.2083 ***
	(17.98)	(15.32)	(13.70)
CONS	−0.3637 *	−0.2141	−0.5282 *
	(−1.68)	(−0.87)	(−1.93)
IND	Yes	Yes	Yes
YEAR	Yes	Yes	Yes
N	9984	7928	6929
R^2	0.2271	0.2358	0.2418
Adj−R^2	0.2196	0.2269	0.2320
F	30.2616	26.5700	24.5109

The number in parentheses in the table is t-statistic; *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

7. Further Discussion

7.1. Heterogeneity Analysis of Property Rights of Enterprises

Digital transformation requires a wide range of resources, such as advanced technology, large-scale investment, and professional talent. Different business properties will have different degrees of impact. State-owned enterprises have abundant resources, technologies and talent and can implement policies in a timely and good manner so that digital transformation can be combined with its original advantages to the greatest extent to truly exert its positive influence and promote the high-quality development of state-owned enterprises. At the same time, due to their special industrial nature, state-owned enterprises undertake heavier tasks of energy conservation and emission reduction and have a strong sense of responsibility, which drives them to be more willing to carry out green technology innovation. To verify the heterogeneity of green technology innovation by the nature of different enterprises, this study divides the sample into state-owned enterprises according to the nature of enterprise property rights and marks them as "1", nonstate-owned enterprises as "0", and adds control variables and controls the annual effect. The effect and industry effect were grouped by regression, and then the differences in coefficients between groups were tested. The regression results are shown in Table 9. Both the digital transformation and green technology innovation of state-owned enterprises and nonstate-owned enterprises are positively significant above the level of 1%, with coefficients of 0.1705 and 0.0985, respectively, and the results of the SUR test showed significant results, indicating that digital transformation promoted green technology innovation in SOEs better than in non-SOEs, thus answering question (3) with data results.

Table 9. Heterogeneity test results based on property rights.

Variable	State-Owned Enterprise	Nonstate-Owned Enterprise
	LNPATENT	
LNDC	0.1705 ***	0.0985 ***
	(12.38)	(13.06)
LNAGE	−0.0161	0.0255
	(−0.30)	(0.91)
CASH	−0.0225	0.2392 ***
	(−0.16)	(3.18)
TOP10	0.6200 ***	−0.2284 ***
	(5.91)	(−3.62)
FAT	−0.5185 ***	−0.2369 ***
	(−4.36)	(−2.74)
GROWTH	−0.0476 ***	−0.0016
	(−2.78)	(−0.14)
LIQUID	−0.0272 **	−0.0082 *
	(−2.32)	(−1.90)
LEV	0.7862 ***	1.0282 ***
	(7.66)	(15.88)
CONS	−0.7398 ***	0.5756 **
	(−2.94)	(2.34)
IND	Yes	Yes
YEAR	Yes	Yes
N	4518	10,164
R^2	0.3750	0.1895
Adj−R^2	0.3626	0.1819
F	30.1991	25.0446
Suest	Chi^2 (1) = 20.07 Prob > Chi^2 = 0.0000	

The number in parentheses in the table is t-statistic; *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

7.2. Heterogeneity Analysis of Firm Size

The practical effect of enterprise digital transformation will be affected by the scale of the enterprise, thus affecting the development of green technology innovation activities. Large enterprises are generally in the middle and upper reaches of the industry, with sufficient funds and strong anti-risk capabilities. Therefore, such enterprises are more likely to carry out digital transformation and have a higher willingness to innovate green technologies. Due to limited resources, technology, talent control, and weak anti-risk capabilities, the digital transformation results cannot be converted into commercial interests on time, which is not conducive to digital transformation to a certain extent. For this reason, this paper takes the mean of the natural logarithm of total enterprise assets as the boundary. If it is greater, it will be assigned as "1" to indicate a large-scale enterprise, and if it is smaller, it will be assigned as "0" to indicate small and medium-sized enterprises. Control variables are added, and the annual effect and industry effect are controlled to carry out group regression and then test the coefficient difference between groups. The regression results are shown in Table 10. Regardless of whether it is a large-scale enterprise or a small or medium-sized enterprise, digital transformation and green technology innovation are both positively significant above the 1% level, with coefficients of 0.1095 and 0.0795, respectively, and the results of the SUR test showed significant results, indicating that digital transformation has a better effect on green technology innovation in large-scale enterprises than in small and medium-sized enterprises, thus answering question (3) with data results.

Table 10. Heterogeneity test results based on firm size.

Variable	Large-Scale Enterprise	Small and Medium-Sized Enterprises
	LNPATENT	
LNDC	0.1095 ***	0.0795 ***
	(9.20)	(11.38)
LNAGE	0.0379	−0.0345
	(0.89)	(−1.34)
CASH	0.5720 ***	0.1081 *
	(4.33)	(1.68)
TOP10	0.3576 ***	−0.3402 ***
	(4.11)	(−5.68)
FAT	−0.4597 ***	−0.4704 ***
	(−4.11)	(−5.96)
GROWTH	−0.0146	0.0189 *
	(−0.87)	(1.79)
LIQUID	−0.0633 ***	−0.0129 ***
	(−4.89)	(−3.60)
LEV	0.8364 ***	0.2504 ***
	(8.67)	(3.91)
CONS	−0.6051 *	0.6139 ***
	(−1.96)	(3.70)
IND	Yes	Yes
YEAR	Yes	Yes
N	6671	8358
R^2	0.3206	0.1411
Adj−R^2	0.3110	0.1313
F	33.3780	14.4370
Suest	Chi^2 (1) = 4.36 Prob > Chi^2 = 0.0368	

The number in parentheses in the table is t-statistic; * and *** indicate significance at the 10% and 1% levels, respectively.

8. Conclusions and Recommendations

8.1. Research Conclusions

Based on the data on the degree of digital transformation of listed companies in Shanghai and Shenzhen A-share companies and the data on green patents from 2007 to 2020, this paper conducts an empirical study. The results of the empirical study show that the digital transformation of enterprises has a significant role in promoting green technology innovation. After testing and overcoming possible endogeneity problems, the above research conclusions still hold. Research on the mechanism of action shows that digital transformation can promote corporate green technology innovation by easing restraints on corporate financing and attracting more government subsidies. Further heterogeneity research also found that the promotion effect of digital transformation on green technology innovation is more significant in state-owned enterprises and large-scale enterprises. The research results are consistent with the research hypothesis proposed above, and the questions raised at the beginning of the paper are solved one by one.

The theoretical significance of this study is that: (1) it makes up for the deficiencies in sample selection in existing studies and expands the existing related studies; (2) it provides a new perspective to explore the mechanism of the role of digital transformation in influencing enterprise green technology innovation; (3) it analyzes the heterogeneity of digital transformation in influencing enterprise green technology innovation based on the nature and scale of enterprise property rights and expands the existing related studies.

The practical significance of this study lies in the following. (1) This paper reveals the mechanism of digital transformation to promote enterprise green technology innovation. It provides corresponding policy enlightenment for the government to further play the promotion role of enterprise digital transformation on green technology innovation to achieve the dual carbon goal. (2) This paper analyzes the heterogeneity of the impact of digital transformation on enterprise green technology innovation in different property rights and enterprises of different sizes, providing the empirical experience for the implementation of government policies. On the one hand, the government can implement targeted policies for different types of enterprises, and on the other hand, it can help the government accurately regulate the implementation effect of policies.

8.2. Countermeasures and Suggestions

This paper not only reveals the impact of enterprise digital transformation on enterprise green technology innovation but also clarifies its mechanism of action and scientifically reveals its heterogeneous effect among enterprises with different characteristics. The level of technological innovation has important policy implications. First, enterprises should improve their awareness of digital transformation, strengthen the construction of data infrastructure, and promote the deep integration of advanced artificial intelligence technology, blockchain technology, cloud computing technology, big data technology and other technologies with the company's business, improve the level of enterprise digitalization, and improve the digitalization of enterprises. This transformation drives the improvement of the green technology level of enterprises. Second, the government should increase financial support for digital transformation enterprises to further break the financing discrimination and financing constraints that are common in the financial market, especially for nonstate-owned enterprises and small and medium-sized enterprises that lack talent, technology, and funds. This policy is inclined to provide financial subsidies for digital transformation, mobilize the willingness and ability of the green technology innovation of such enterprises, and improve the overall efficiency of green technology innovation. Third, financial institutions should reasonably lower the financing threshold so that more private enterprises and small and medium-sized enterprises can obtain funds and provide financial support for the digital transformation of private enterprises and small and medium-sized enterprises, thereby promoting the improvement of enterprises' green technology innovation level.

Author Contributions: Conceptualization, L.X. and Q.Z.; data curation, Q.Z.; formal analysis, L.X. and Q.Z.; funding acquisition, L.X., Q.Z. and X.Z.; methodology, Q.Z. and L.X.; software, Q.Z.; supervision, L.X.; writing—original draft, Q.Z. and L.X.; writing—review and editing, Q.Z., L.X., C.L. and X.Z.; resources, C.L. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by National Office for Philosophy and Social Sciences of China (21CJL006); The Key Scientific Research Projects of Colleges and Universities of Henan Province (22A790024); National Natural Science Foundation of China (71803181); Science and Technology Innovative Talents (Humanities and Social Sciences) Program of Henan (2021-CX-019); Key R&D and Pro-motion Project of Henan (Soft Science Research) (222400410123).

Informed Consent Statement: Not applicable.

Data Availability Statement: The data presented in this study are openly available in the Chinese Research Data Services Platform and the China Stock Market Accounting Research Database (CSMAR).

Conflicts of Interest: The authors declare no conflict of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript, or in the decision to publish the results.

References

1. Li, Y. Research on Green Recovery and Green Technology Innovation. *J. Tianjin Norm. Univ.* **2021**, *4*, 105–110.
2. Hu, A.G. China's goal of carbon peak by 2030 and main approaches. *J. Beijing Univ. Technol.* **2021**, *21*, 1–15.
3. Chen, J.D.; Wang, J.J. Digital input and manufacturing innovation efficiency. *Econ. Surv.* **2022**, *39*, 78–88.
4. Feroz, A.K.; Zo, H.; Chiravuri, A. Digital Transformation and Environmental Sustainability: A Review and Research Agenda. *Sustainability* **2021**, *13*, 1530. [CrossRef]
5. Warner, K.S.R.; Wäger, M. Building dynamic capabilities for digital transformation: An ongoing process of strategic renewal. *Long Range Plan.* **2018**, *52*, 326–439. [CrossRef]
6. Liu, D.Y.; Chen, S.W.; Zhou, Z.C. Resource fit in digital transformation. *Manag. Decis.* **2012**, *49*, 1728–1742. [CrossRef]

7. Matarazzo, M.; Penco, L.; Profumo, G.; Quaglia, R. Digital transformation and customer value creation in Made in Italy SMEs: A dynamic capabilities perspective. *J. Bus. Res.* **2021**, *123*, 642–656. [CrossRef]
8. Li, L.; Su, F.; Zhang, W.; Mao, J.Y. Digital transformation by SME entrepreneurs: A capability perspective. *Inf. Syst. J.* **2018**, *28*, 1129–1157. [CrossRef]
9. Li, H.L.; Wu, Y.; Cao, D.M.; Wang, Y.C. Organizational mindfulness towards digital transformation as a prerequisite of information processing capability to achieve market agility. *J. Bus. Res.* **2021**, *122*, 700–712. [CrossRef]
10. Borowski, P.F. Digitization, Digital Twins, Blockchain, and Industry 4.0 as Elements of Management Process in Enterprises in the Energy Sector. *Energies* **2021**, *14*, 1885.
11. Tu, X.Y.; Yan, X.L. Digital transformation, knowledge spillover and total factor productivity: Empirical evidence from listed manufacturing companies. *Ind. Econ. Res.* **2022**, *2*, 43–56.
12. Hajli, M.; Sims, I.M.; Ibragimov, V. Information technology (IT) productivity paradox in the 21st century. *Int. J. Product. Perform. Manag.* **2015**, *64*, 457–478. [CrossRef]
13. Qi, Y.D.; Cai, C.W. Research on the multiple effects of digitalization on the performance of manufacturing enterprises and its mechanism. *Study Explor.* **2020**, *7*, 108–119.
14. Porter, M.E.; Linde, C.V.D. Green and competitive: Ending the stalemate. *Harv. Bus. Rev.* **1995**, *73*, 120–134.
15. Guo, Y.; Xia, X.; Zhang, S.; Zhang, D. Environmental Regulation, Government R&D Funding and Green Technology Innovation: Evidence from China Provincial Data. *Sustainability* **2018**, *10*, 940.
16. Hong, M.; Li, Z.; Drakeford, B. Do the Green Credit Guidelines Affect Corporate Green Technology Innovation? Empirical Research from China. *Int. J. Environ. Res. Public Health* **2021**, *18*, 1682. [CrossRef]
17. Luo, Y.; Salman, M.; Lu, Z. Heterogeneous impacts of environmental regulations and foreign direct investment on green innovation across different regions in China. *Sci. Total Environ.* **2021**, *759*, 143744. [CrossRef]
18. Yi, M.; Fang, X.; Wen, L.; Guang, F.; Zhang, Y. The Heterogeneous Effects of Different Environmental Policy Instruments on Green Technology Innovation. *Int. J. Environ. Res. Public Health* **2019**, *16*, 4660. [CrossRef]
19. Lv, C.C.; Shao, C.H.; Li, J.J. Green technology innovation and financial development: Do environmental regulation and innovation output matter? *Energy Econ.* **2021**, *98*, 105237. [CrossRef]
20. Tang, C.; Xu, Y.Y.; Hao, Y.; Wu, H.T.; Xue, Y. What is the role of telecommunications infrastructure construction in green technology innovation? A firm-level analysis for China. *Energy Econ.* **2021**, *103*, 105576. [CrossRef]
21. Palčič, I.; Prester, J. Impact of Advanced Manufacturing Technologies on Green Innovation. *Sustainability* **2020**, *12*, 3499. [CrossRef]
22. Ma, Y.; Zhang, Q.; Yin, Q. Top management team faultlines, green technology innovation and firm financial performance. *J. Environ. Manag.* **2021**, *285*, 112095. [CrossRef] [PubMed]
23. Wang, F.Z.; Liu, X.L.; Zhang, L.; Cheng, W.C. Does digitalization promote green technology innovation in resource-based enterprises? *Stud. Sci. Sci.* **2022**, *40*, 332–344.
24. Song, D.Y.; Zhu, W.B.; Ding, H. Can enterprise digitalization promote green technology innovation? —Based on the investigation of listed companies in heavy pollution industries. *J. Financ. Econ.* **2022**, *48*, 34–48.
25. Li, D.K.Q.; Shen, W.T. Can Corporate Digitalization Promote Green Innovation? The Moderating Roles of Internal Control and Institutional Ownership. *Sustainability* **2021**, *13*, 13983. [CrossRef]
26. Ghasemaghaei, M.; Calic, G. Assessing the impact of big data on firm innovation performance: Big data is not always better data. *J. Bus. Res.* **2020**, *108*, 147–162. [CrossRef]
27. Jin, F.; Qi, Z.H.; Liang, Y.L. Big Data, Financial Agglomeration and Green Technology Innovation. *Rev. Econ. Manag.* **2021**, *37*, 97–112.
28. Borowski, P.F. Innovation strategy on the example of companies using bamboo. *J. Innov. Entrep.* **2021**, *10*, 3–20. [CrossRef]
29. Baumann, J.; Kritikos, A.S. The link between R&D, innovation and productivity: Are micro firms different? *Res. Policy* **2016**, *45*, 1263–1274.
30. Brown, J.R.; Martinsson, G.; Petersen, B.C. Do Financing Constraints Matter for R&D? *Soc. Sci. Electron. Publ.* **2012**, *56*, 1512–1529.
31. Yang, G.Z.; Xi, Y.T. An Empirical Study on Financing Constraints of Enterprise Green Technology Innovation Activities. *J. Ind. Technol. Econ.* **2019**, *38*, 70–76.
32. Zhai, H.Y.; Liu, Y.S. Research on the relationship between digital finance development, financing constraints and enterprise green innovation. *Sci. Technol. Prog. Policy* **2021**, *38*, 116–124.
33. Jiang, J.X.; Tang, Y.C.; Li, X.J. Digital Finance Empowers Green Innovation of New Energy Enterprises under the Background of Double Carbon: Based on the Perspective of Financing Constraints. *Contemp. Econ. Manag.* **2022**, *44*, 1–19.
34. Yao, P.Y. Research on the impact path of government subsidies on the innovation of small and medium-sized enterprises. *Technol. Econ.* **2022**, *41*, 26–37.
35. Wang, W.T.; Cao, D.D. Internet capital and high-quality development of private economy: Based on the perspective of enterprise innovation-driven path. *Stat. Res.* **2020**, *37*, 72–84.
36. Li, W.J.; Zheng, M.N. Substantive innovation or strategic innovation?—The impact of macro-industrial policy on micro-enterprise innovation. *Econ. Res. J.* **2016**, *51*, 60–73.
37. Wu, F.; Hu, H.Z.; Lin, H.Y.; Ren, X.Y. Enterprise digital Transformation and capital market performance: Empirical evidence from stock liquidity. *Manag. World* **2021**, *37*, 15.

38. Hadlock, C.J.; Pierce, J.R. New Evidence on Measuring Financial Constraints: Moving Beyond the KZ Index. *Rev. Financ. Stud.* **2010**, *23*, 1909–1940. [CrossRef]
39. Zhao, T.; Zhang, Z.; Liang, S.K. Digital economy, entrepreneurial activity and high-quality development: Empirical evidence from Chinese cities. *Manag. World* **2020**, *36*, 65–76.