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Research on the Impact of Digital Transformation of Enterprises on Green Innovation Technology

-- Based on big language modeling

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Abstract: With the vigorous development of the Internet and emerging production technologies, digital economy as a new type of economic form has shown vigorous development, injecting new momentum into the evolution of the traditional economic structure of society. Based on promoting the realization of the "double carbon" goal and accelerating the construction of a new type of energy economic system, this study is based on a large language model, using the data from the annual reports of China's A-share listed companies from 2013-2023 to build a corpus, to further measure the level of digital transformation of enterprises, to construct a digital transformation index system, and to explore the impact of digital transformation on green innovation technology. impact of green innovation technology. According to the results of empirical analysis, the R&D capability, profitability, and dynamic ability of companies in digital transformation effectively motivate the research of green innovation technology.

Keywords: Digital Transformation, Green Innovation Technology, Big Language Modeling.

1. Introduction

With the transformation of the economic landscape, energy shortage and environmental pollution have gradually become important issues facing the high-quality development of the modern economy, and the government and the state attach great importance to integrating green innovation into the new development landscape. In terms of policy inclination, in 2020, the state proposed in the Fifth Plenary Session of the 19th CPC Central Committee to enterprises to "deepen the innovation-driven strategy and promote the high-end, intelligent, and greening of traditional industries," which required enterprises to promote the transformation of traditional industries to modern industries.In2021, the State Council issued a program to support enterprises to implement the national key projects of green low-carbon technology and support enterprises to promote the green low-carbon technology revolution.In 2022, the National Development and Reform Commission issued a program that includes 70 national standards for carbon emission reduction, carbon accounting, carbon footprinting, carbon capture, energy efficiency, and utilization and sequestration, requiring enterprises to basically reach the international green level in terms of product energy consumption and energy efficiency technical indexes.TheNational Development and Reform Commission also issued a program to support enterprises to promote the transformation of traditional industries into modern industries. The government's and the state's support for high-quality development and the direction of support have become increasingly obvious. Studying the impact of enterprise digital transformation on green innovation technology is a concrete reflection on actively following the development direction of the Party and the State, and accelerating the construction of a new type of energy system by promoting the realization of the goal of "double carbon".

In recent years, more research on digital transformation has been conducted in the academic world, and fruitful results have been achieved, but the current research focuses on individual, qualitative case studies, does not return to the specific use of the practice, and the conclusions are not uniform and lack of universality. This paper intends to take data related to the development of green innovation technology in China's*A* listed companies in the past 10 years as a research sample to assess the impact of digital transformation on green innovation technology, which will help improve the theoretical system of related research and provide a theoretical basis and guiding ideas for the development of green innovation technology in enterprises.

At present, resource shortage and environmental pollution have become important problems facing the high-quality development of modern economy, and the sustainable development of the economy lacks intrinsic motivation. In the face of this serious situation, it is necessary to integrate green development into enterprise development and gradually realize carbon emission reduction. Green innovation technology is an important support and guarantee for the development of green economy in the context of digital transformation. Sorting out the internal connection and effective articulation of digital transformation and green innovation technology development, finding common problems and deep-rooted problems, and grasping the wind direction of this historic innovation revolution are of great significance for the specific work and top-level design of enterprises to realize the green transformation of enterprises, the development of low-carbon economy, and the promotion of beautiful China.

2. Level of Digital Economy and Digital Transformation Measurement

Since 2023, China's economy has withstood the challenges of risks from the weakening global economy, industrial chain adjustments, and regional conflicts, and mitigated the adverse impacts from the lack of confidence in the domestic market, the fall in domestic demand, and the contraction of external demand, and overall realized a long-term economic upturn. Data from the National Bureau of Statistics (NBS) showed that China's annual GDP grew by 5.2% in real terms at constant prices, with the economic growth rate further picking up in line with the potential growth level of the economic forecast. Against this backdrop, new progress has been made in the high-quality development of China's digital economy, and the digital digital transformation capacity of enterprises has been further enhanced, entering a new stage of leading development in a new round.

2.1. Level of Development of the Digital Economy, 2013-2023

2.1.1. Rapid Development of the Digital Economy

The digital economy, with digital resources as the key production factor, information and communication technology as the gripping hand, and information networks as the important carrier, is driving the development of the modern economy. Since the 18th Party Congress, China's digital economy has entered a rapid development cycle with favorable policies. It can be seen that the scale of the digital economy grew from 11.2 trillion yuan in 2012 to 53.9 trillion yuan in 2023, with an average annual growth rate of 14.8%; while China's GDP grew at an average annual rate of 7.6% during the same period, the average annual growth rate of the scale of the digital economy is about 7.2 percentage points higher than the average annual growth rate of the GDP. 2022, under the stimulation of a series of favorable policies of the Party Central Committee ,the scale of the national digital economy grew by 10.3% year-on-year, accounting for 41.5% of GDP, higher than the growth rate of GDP in the same period by 5 percentage points. The speed of its development is unprecedented, and it is becoming a key force in reshaping the new economic pattern.

2.2. Digital Transformation 2013-2023 Level of Development

2.2.1. Digital Transformation of Enterprises Steady Progress

The digital economy, with its higher level of technology, stronger innovative capacity, greater penetration and wider scope of radiation drive, is rapidly promoting the comprehensive digital and intelligent transformation of the economy and society, and is of great significance in enhancing the capacity for scientific and technological innovation, constructing a modernized industrial system, and advancing the high-quality development of the economy. With favorable policies and support from the whole society, the modern economy is steadily transforming into a digital economy.

The proportion of listed companies using digital technology is as high as about 92%. According to the official data disclosed by the Bureau of Statistics, as of 2023, 4,722 listed companies are using digital technology, with the proportion of using digital technology reaching 91%, and a total of 1,718 listed companies in the digital economy industry nationwide , of which 893 are listed on the main board, 554 are listed on the Growth Enterprise Market (GEM) board, 227 are listed on the Science and Technology Innovation Board (STEB) board, and 44 are listed on the Bejing Stock Exchange (BSE).

2.3. Differences in the Development of the Digital Economy and Digital Transformation

2.3.1. Digital Transformation Industry Differences

The full integration of the Internet and digital technology has achieved reasonable quantitative growth and effective qualitative improvement, and promoted the transformation of the real economy into digitalization. Since the 18th National Congress of the Party, the foundation for the integration and development of China's digital economy and real economy has been further consolidated, and the degree of integration has continued to expand and deepen. However, there are significant differences in the proportion of digitization in different industries. The trend of digitization in the service industry is remarkable, and the communication, banking, computer and other industries a fully realized digitization, while the digital proportion of manufacturing and real estate is lower. Specifically, the top five industries with the highest proportion of digitized enterprises are communications, banking, computers, media, electronics; the five industries with the lowest proportion of digitized enterprises are petroleum and petrochemicals, non-ferrous metals, basic chemicals, coal, real estate.

2.3.2. Regional Differences in Digital Transformation

In this paper, the digital economy index of different provinces is counted, and the digital economy index is used to indicate the degree of digital transformation. Statistics show that since 2023, the development of digital economy in various regions has presented some new features, and regions with better economic foundation and stronger scientific and technological innovation ability have fully released the effect of economy of scale and economy of scope, and the digital economy has realized faster, better and more resilient development. Combined with the analysis of the market scale of digital transformation in recent years, East China and North China are the main markets for digital transformation in China; the digital economy index of Beijing, Shanghai, Jiangsu, Guangdong and other provinces and cities has exceeded 40, and the development of the digital economy in Beijing and Shanghai is close to the level of the United States, Europe and other developed countries.

3. Theoretical Analysis and Research Hypotheses

3.1. Digital Transformation and Green Innovative Technologies

Currently, digital transformation has a significant role to play in green innovation technology. Digital transformation empowers enterprises to cultivate new quality productivity, facilitates enterprises to stand on the scientific and technological frontiers of the times, and improves the efficiency of innovation. Enterprises through the implementation of digital transformation, can make efficient use of big data and other digital technology advantages, and then significantly improve the speed of information acquisition and analysis and timely grasp of innovation resources data, promote internal and external information sharing and collaboration, through the digital R & D platform enterprises can optimize the integration of innovation resources, elements of the configuration, and then help enterprises to better identify the market changes and trends in the scientific and technological environment for the development and promotion of green products provide a basis to help actively seize the opportunities of green development. This helps enterprises better identify market changes and trends in the scientific and technological environment, provides a basis for the development and promotion of green products, and helps them actively grasp the opportunities of green development. At the same time, enterprises utilize digital information to formulate green innovation transformation paths in line with their own development needs and resource reserves, which can correctly guide the direction of green innovation R&D, develop products that better meet environmental protection requirements, reduce the risk of failure, control the cost of innovation, upgrade the innovation process, and promote breakthroughs in key green technologies and enhance innovation efficiency. Based on this, the first hypothesis of this paper is formulated:

Digital transformation has a positive impact on green innovation technologies.

3.2. Research and Development Capacity and Green Innovation Technology Development

R&D investment is the core of enterprise technology innovation, which not only includes the exploration and development of new technologies, but also involves the optimization and upgrading of existing technologies. In the context of digital transformation, R&D investment of enterprises is closely related to the development of green innovation technology of enterprises. R&D investment can provide enterprises with capital, talent and technology accumulation, which is the key to the development of green innovation technology. Digital transformation itself is a technology-driven process, which requires enterprises to continuously invest resources in improving their R&D capabilities, exploring and applying new technologies, new methods and new models. According to the literature study, it is known that among different types of enterprises and regions, there is a significant difference in the promotion of digital transformation on green innovation due to different research inputs, especially in state-owned enterprises, high-tech enterprises, and those in the central region, and this effect is more significant. Meanwhile, based on the analysis of the large language model, enterprises with a growing trend of "R&D investment and growth" have a higher proportion of digital technology use and digital use. Based on this, the second hypothesis of the paper is formulated:

There is a positive correlation between firms' R&D capabilities and firms' green innovation technologies.

3.3. Profitability and Green Innovation Technology Development

Profitability is an important indicator for assessing the operational efficiency and development level of an enterprise, as well as for assessing the performance of an enterprise's digital transformation. In general, enterprise digital transformation and profitability go hand in hand. Better profitability enables enterprises to make sufficient investment in technology and high-quality resource allocation, improves overall operational efficiency, promotes digital exploration, facilitates the effective implementation of green technology programs, and provides a good research environment for green innovative technologies. On the other hand, digital transformation can positively guide the decision-making behavior of enterprises, so that they can make timely decisions in line with the current green development, and promote the improvement of their own profitability. At the same time, better profitability strengthens the enterprise's anti-risk ability, so that the enterprise's green innovation technology field of vitality to produce continuity, stability, effectiveness. Based on this, the third research hypothesis of this paper is proposed:

Profitability promotes green and innovative technologies in companies.

3.4. Dynamic Capabilities and Green Innovative Technologies

Dynamic capability, as an important capability of enterprises in the environment of digital development, refers to the ability of enterprises to integrate internal and external resources to cope with risks in a rapidly changing market environment. In the process of enterprise digital transformation, the use of digital technology facilitates the change of enterprise management structure, which directly leads to the enhancement of enterprise dynamic ability, promotes the timeliness and accuracy of enterprise decision-making, and improves the operational efficiency and organizational performance of enterprises. At the same time, relying on digital technology to improve the horizontal management and collaboration capacity of enterprises, improve management efficiency, and promote production and operation to better obtain the core competitive position. Based on this, the fourth hypothesis of the paper is formulated:

Dynamic capabilities in corporate digital transformation are positively correlated with corporate green innovation technology.

In summary, this paper proposes four research hypotheses based on literature and theoretical analysis.

Hypothesis 1: Digital transformation has a positive effect on green innovation;

Hypothesis 2: There is a correlation between firms' R&D capabilities and firms' green innovation technologies;

Hypothesis 3: Firms' profitability promotes firms' green innovation technology;

Hypothesis 4: Firms' dynamic capabilities can have an impact on the green innovation technology;

4. Research Methodology and Design

Through the above theoretical analysis, this paper puts forward relevant theoretical research hypotheses. In order to verify the above hypotheses, this paper takes the A-share listed companies of Chinese companies from 2013 to 2023 as the research object.

4.1. Selection of Variables and Data Sources

4.1.1. Data Sources

Based on the availability of data and sample comparability, in the research and analysis process of this paper, Hong Kong, Macao, Taiwan and Tibet are excluded, and listed enterprises distributed in the rest of China's 30 provinces are selected as research objects. Since the 18th National Congress of the Communist Party of China (CPC), the green and low-carbon development of enterprises has seen rapid development under the support of the CPC and the state. Therefore, the time span of the study is 2013-2023. The sample data are mainly from China Knowledge Network, National Bureau of Statistics, China Statistical Yearbook, China Industrial Statistical Yearbook, and the number of green patent applications are from State Intellectual Property Office. This paper selects China's A-share listed companies as the research object from 2013 to 2023, and refers to the existing literature to process the raw data according to the following methods: (1) exclude ST (special treatment), *ST (delisting warning) and PT enterprises; (2) exclude the companies with zeroes in the numbers of "patent applications" and "R&D investment"; (3) exclude the companies with zeroes in the numbers of "patent applications" and "R&D investment". (2) Excluding enterprises whose "patent applications" and "R&D investment" are all zero; (3) Excluding other observations with serious missing variables. After the above processing, there are 2,536 enterprises, totaling 33,900 sample observations. In this paper, the selected variables are subjected to Winsorizationof the upper and lower 1% to reduce the negative impact of outliers and extreme values on the results.

4.1.2. Selection of Variables

In this paper, seven variables were selected in conjunction with the existing literature: one explanatory variable, three explanatory variables, two control variables, and one mediating variable. The names of the variables are shown in Table 1:

Table 1. Related Variables

Variable type	variable name	Variable Meaning
explanatory variable	Green patent applications	Ln (number of green patents+1)
explanatory variable	R&D capacity	Enterprise R&D investment as a percentage of operating revenue
	Profitability	Net profit margin on total business assets
	Dynamic capacity	Firms' human capital as a share of assets
intermediary variable	Level of industrial integration	Total business assets/GNP
control variable	Enterprise size	Ln (total assets of the enterprise)
	Capital intensity	Ln (total business assets/operating income)

(1) Explained Variables. The explanatory variable of this project study is green innovation technology efficiency (G). This project draws on the measurement methods of green innovation technology in the academic world and uses text analysis to mine the indicators of green innovation technology. This paper organizes the green patent data published by the National Bureau of Statistics and the World Intellectual Property Office to obtain the number of green invention patents and green utility patents applied by enterprises in each year, and measures green innovation output with the help of the total number of green patents applied by enterprises. The green innovation technology is measured by the green patent applications of listed companies, i.e. the total number of green patent applications plus 1 is expressed as the natural logarithm of the total number of green patent applications.

(2) Explanatory variables. In order to exclude the interference of other factors on the conclusion of the research this project on the basis of theoretical analysis, selected a series of control variables (X). According to the research, green innovation technology occurs in larger enterprises at the beginning, the larger the enterprise size (S), the more resources it owns, the deeper the influence on the enterprise's green innovation technology. The higher the capital intensity (C), the more prominent the enterprise's resource advantage, the more favorable to sustain green innovation technology.

(3) Mediating variables. In order to make the research conclusions more accurate, this paper selects the level of industrial integration as the mediating variable. Generally speaking, the higher the level of industrial integration, the greater the degree of influence on the level of digital transformation, which in turn positively affects the efficiency of the level of green innovation.

4.2. Modeling

4.2.1. Large Language Model ERNIE

Based on and better reflecting the use of various digital technologies in enterprises, this paper utilizes big language modeling and machine learning methods to collect the annual reports of 5,765 listed companies in China from 2013 to 2023 to construct digital transformation indicators for listed companies. The construction of indicators for digital transformation is carried out in five steps:

The first step is to download the annual reports of listed companies from specialized websites, and use the chapter "Management Discussion and Analysis" in the annual reports as the textual basis for constructing the digital transformation indicators.

In the second step, the relevant texts are all segmented into sentences according to periods and semicolons to constitute the library of sentences to be tested. In order to reduce the unnecessary interference of context on manual reading, different annual report sentences represented by the help of keywords and with randomly selected sentences constitute the library to be labeled. Synthesizing the existing literature and relevant announcements of the National Bureau of Statistics, digital technologies are divided into six types: artificial intelligence, mobile Internet, big data, Internet of Things, cloud computing, and blockchain, and the dictionary of digital technologies is constructed to obtain the to-be-tagged sentence bank of this study.

In the third step, the above keywords of the to-be-tagged sentence bank are manually labeled and used to determine whether the enterprise has undergone digital transformation.

In the fourth step, ERNIE, a large language model, is utilized to pre-train the sentences for supervised classification. The machine learning metrics are trained to measure digital transformation, and AI technology is used as a keyword to discriminate whether the inclusion of digital technology keywords in the text is a real digital transformation of the enterprise, so as to alleviate the difficulty of mentioning the keywords of digital technology in the text, but not actually using digital technology.

In the fifth step, the trained ERNIE model is used to make sentence-by-sentence prediction of the sentence bank to determine whether listed companies use and which type of digital technology they use. In this paper, enterprise digital transformation is constructed as a variable, i.e., if a listed company uses any one of the six types in the current year, it is assigned a value of 1, and vice versa is 0. Based on the data, we get the digital technology descriptive statistics Table 2.

Table 2. Digital Technical Descriptive Statistics

	N	N (non-empty)	max	min	average value
statistical year	41667	41667	--	--	--
stock code	41667	41667	--	--	--
artificial intelligence (AI) technology	41667	41667	401	0	2.3178
blockchain technology	41667	41667	39	0	0.0674
Cloud Computing Technology	41667	41667	390	0	3.3804
Bigdata technology	41667	41667	296	0	2.9085
Digital technology applications	41667	41667	419	0	5.4557

Briefly,this paper takes 42,131 annual report texts of Chinese A-share listed companies from 2013 to 2023 as the object of analysis. A dictionary of keywords about digital technologies is constructed and digital technologies are categorized into six types: artificial intelligence, mobile internet, big data, internet of things, cloud computing, and blockchain. Next, the annual reports were manually labeled to form a training set. After that, supervised machine learning methods were used to screen the annual reports with the help of the EERNIE big language model developed by Baidu to determine whether the companies used digital technologies and what kind of digital technologies were used, and at the same time constructed a digital transformation visualization index for the listed companies in China's A stock market based on the data that support digital transformation in the financial statements. As shown in the figure, this paper selects R&D investment expenditures (R&D capability), profitability, and talent investment (dynamic capability) as indicators to explain digital transformation. Among them, based on the existence of differences in industries and regions in digital transformation, the level of industrial integration is selected as a control variable.

4.2.2. LDA Model

This project studies the construction of evaluation indexes of green innovation technology, due to the fact that the existing literature on green innovation technology is less research, less sample data can be obtained, so it adopts the LDA model (Latent Dirichlet Allocation) to conduct text analysis. As shown in Figure 8, the LDA model is a typical directed probability map model, determined by the parameter (α,β) , α reflects the relative strengths and weaknesses of the implied themes in the document set, and β depicts the probability distribution of all the implied themes themselves. Among them, θ_k denotes the probability distribution of document topics,φ_k denotes the probability distribution of feature words,M denotes the number of texts in the document set,K denotes the number of topics in the document set, and$N$ denotes the number of feature words contained in each document.

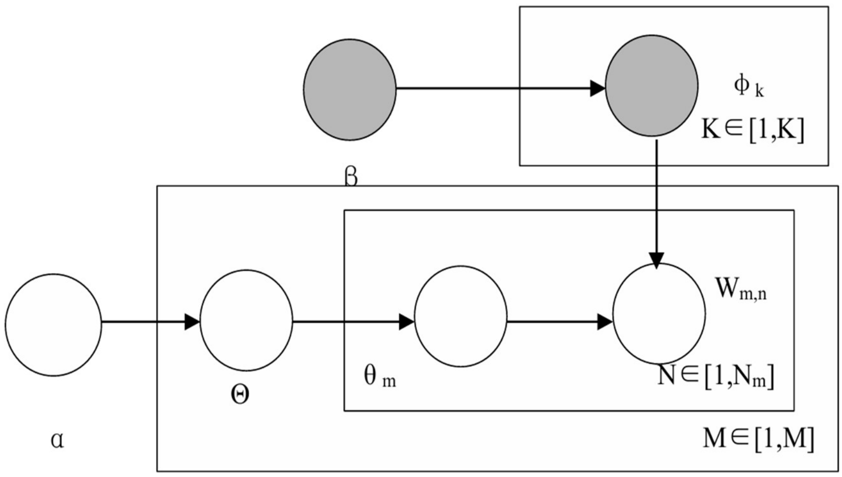

Figure 1. Detail of LDA model

4.2.3. Logistics Multiple Regression

This project investigates the impact of digital transformation on green innovation technology, which involves multiple independent variables and multiple dependent variables, so a multivariate hierarchical panel regression model is used using Stata16 software. The following model is set to conduct the regression test:

$$Y = a_0 + a_1 Dig_{it} + a_2 X_{it} + \mu_i + \varepsilon_{it} \tag{1}$$

Y stands for the level of green innovation technology; istands for enterprises; t stands for year;a_0 ,a_1 ,a_2 stand for the intercept term, the coefficient of influence of the explanatory variables and the coefficient of influence of the control variables, respectively; X_i stands for the digital transformation;β_i stands for the set of control variables;μ_i stands for the error in the level of regional development, andε_{it} stands for the stochastic perturbation term.

4.2.4. Mediating Effects Model

On the basis of analyzing the impact of digital transformation on green innovation technology, this project further applies the mediated utility model to examine the transmission path of industrial integration level and dynamic capability when digital transformation affects enterprises' green innovation technology. The regression equations are as follows:

$$M = \beta_0 + \beta_1 Dig_{it} + \beta_2 X_{it} + \mu_i + \varepsilon_{it} \quad (2)$$

$$Y = \lambda_0 + \lambda_1 Dig_{it} + \lambda_2 M_{it} + \lambda_3 X_{it} + \mu_i + \varepsilon_{it} \quad (3)$$

Where M denotes the mediating variables industrial integration level and dynamic capabilities examined in this project, and the other variables conform to the same economic meanings as in the above model.

5. Empirical Analysis and Testing of Results

5.1. Descriptive Statistics

This paper takes the financial data of Chinese A shares listed companies from 2013 to 2023 as the research object. After screening and processing to get the variable description statistics Table 3, the overall sample size is 33,900, the data is basically characterized by normal distribution, but the difference between the data is large. The maximum value of the explanatory variables is 3.7612, the minimum value is 0, the difference between the values is small, indicating that the difference between the enterprises of the green innovation technology is not large; from the explanatory variables, control variables, look at the R & D capability, capital intensity, and profitability of the minimum and maximum values, the difference between the data is large, the data is high degree of discretization, indicating that due to the reality of the operating situation of the differences between the different enterprises of the R&D capability, capital intensity, and profitability. ability, capital intensity, and profitability are different among different enterprises due to different real business situations. In terms of the mediating effect played by the level of industrial integration, the difference between the maximum value and the minimum value is large, indicating that due to the industry barriers the level of industrial integration between different enterprises is different, and the degree of influence on the operational efficiency of enterprises is different, some of them can realize the industrial restructuring in the process of digital transformation and realize the enhancement of green innovation and technology, while some of them are vice versa.

Table 3. Variable Descriptive Statistics

variant	Number	average value	SD	min	max
Green Innovation Application	33900	0.3477425	0.724626	0	3.7612
R&D capability	33900	0.757243	0.0468302	0	193.252
profitability	33900	0.0369103	0.0527219	0.245307	108.3657
dynamic capability	33900	0.070408	0.0467328	0.004161	2.493746
Enterprise size	33900	22.25676	1.360996	15.97917	28.69688
capital intensity	33900	5.87293	351.2373	0.0718725	59623.31
Level of industrial integration	33900	4.726128	28.63127	0	443.4165

5.2. Correlation Analysis

In this paper, one explanatory variable (G), three explanatory variables (P, R, D), and two control variables (S, I) were selected for correlation analysis based on the results of literature analysis. One mediating variable (C) was also selected for mediation effect analysis. The results of correlation among variables are shown in Table 4. Under the condition of significance level of 0.05, the relationship between the explained variable(G) and the explanatory variables (P, R, D) is positive, which verifies the research theoretical hypotheses 2, 3, and 4. The relationship between the mediating variable (C) and the explanatory variables (R, D) is positive, which indicates that the mediating variable can play a certain role on the explanatory variables in the model.

Table 4. Correlation coefficient matrix

	G	P	R	D	S	I	C
G	1.000						
P	0.0340	1.0000					
R	0.0157	-0.0505	1.0000				
D	0.0520	0.0763	0.1530	1.0000			
S	0.1233	-0.0697	-0.2629	-0.2690	1.0000		
I	-0.0353	-0.1557	0.2724	-0.3222	-0.0028	1.0000	
C	0.318	-0.0231	0.0328	0.0187	0.0895	-0.0220	1.0000

5.3. Multicollinearity Test

In order to ensure the accuracy of the model, this paper tests the existence of multicollinearity between the explanatory variables selected in this paper with the help of state16. According to the empirical method, the magnitude of the value of variance inflation factor (VIF) reflects the degree of covariance between the variables. Generally, when 0<VIF<10, it indicates that there is no multicollinearity between variables; when 10 ≤ VIF<100, it indicates that there is a strong covariance between variables; and when VIF ≥ 100, it indicates that there is a serious covariance between variables. The test results of this paper are shown in Table 5, the VIF of all variables are less than 10, and the tolerance (1/VIF) is between 0-1, which indicates that the covariance between the variables is within the acceptable range and can explain the relationship of the model well, that is to say, there is no multicollinearity between the variables selected in this paper.

Table 5. VIF Relationship Diagram

Variable	VIF	1/VIF
I	1.29	0.778117
D	1.27	0.789154
R	1.21	0.823687
S	1.14	0.873952
P	1.03	0.969767
Mean VIF	1.19	/

5.4. Multiple Regression Results

This paper utilizes a regression analysis with fixed effects, where the explanatory variables are taken 100 times in order to reduce the differences between the data and get better regression results. The regression results are shown in Table 6.

Table 6. Multiple Regression Results

Source	ss	df	MS	Number of		31.508
Model	437.298836	5	87.4597672	F (5, 31502)		169.49
Residual	16255.6196	31, 502	0.516018652	Prob > F		0.0000
Total	16692.9184	31, 507	0.529816181	R-squared		0.0262
				Adj R-squared		0.0260
				Root MSE		0.71834
G	Coefficient	Std.err	t	P>|t|	[95%conf.	Interval]
P	0.5308324	0.0784301	6.77	0.000	0.3771064	0.6845584
R	0.7956457	0.0965632	8.24	0.000	0.6063781	0.9849133
D	1.236462	0.0985657	12.54	0.000	1.04327	1.429655
S	0.0874412	0.0032617	26.81	0.000	0.0810482	0.938343
I	-0.0838335	0.0031363	-2.67	0.000	0.0145308	-0.0022362
_cons	-1.747376	0.772989	-22.61	0.000	-1.898885	-1.595867

According to the regression data in the table, the following conclusions can be drawn, the relationship between digital transformation and green innovation technology is positive. In particular, at the significance level of 0.05, the increase in the level of green innovation technology is positively correlated with the increase in profitability, R&D investment, and dynamic capabilities. Profitability, R&D investment, and dynamic capability can positively and positively influence the green innovation technology of enterprises.

5.5. Intermediation Effects

In this paper, the mediating role of industrial integration level (C) in digital transformation (P, R, D) and green innovation technology(G) is tested by stepwise regression method. Firstly, we test the effect of digitalization level on industrial integration level, and then we introduce the mediating variable (C) in the regression model to test its mediating effect, and the results are shown in Table 7.

Table 7. Intermediary effect results

Source	ss	df	MS	Number of		31, 469
Model	356364.487	5	71272.8975	F (5, 31502)		90.08
Residual	24894428.8	31, 463	791.228706	Prob > F		0.0000
Total	252500973.3	31, 468	802.467649	R-squared		0.0141
				Adj R-squared		0.0140
				Root MSE		28.129
C	Coefficient	Std.err	t	P>|t|	[95%conf.	interval]
P	-11.02603	3.07529	-3.59	0.000	-17.05372	-4.99834
R	40.78012	3.79029	10.76	0.000	33.35101	48.20924
D	18.76396	3.863259	4.86	0.000	11.19181	26.3361
S	2.398021	0.1269716	18.89	0.000	2.149152	2.646891
I	-0.6360563	0.1229705	-5.17	0.000	0.8770832	-0.3950293
_cons	-51.3581	3.010789	-17.06	0.000	-57.25936	-45.45683

Table 8. Stepwise regression results

Source	ss	df	MS	Number of		31, 196
Model	443.865176	6	73.9775294	F (5, 31502)		143.85
Residual	16039.9655	31, 189	0.514282777	Prob > F		0.0000
Total	16483.8307	31, 195	0.528412589	R-squared		0.0269
				Adj R-squared		0.0267
				Root MSE		0.71714
G	Coefficient	Std.err	t	P>|t|	[95%conf.	Interval]
C	0.0003832	0.0001445	2.65	0.000	0.0001001	0.0006663
P	0.5457464	0.0786141	6.94	0.000	0.3916595	0.6998332
R	0.8167825	0.0972577	8.40	0.000	0.6261536	1.007411
D	1.226674	0.0989305	12.40	0.000	1.032766	1.420582
S	0.0878427	0.0033171	26.48	0.000	0.0813409	0.0943444
I	-0.0086623	0.0031487	-2.75	0.000	-0.0148338	0.0024908
_cons	-1.758197	0.0784444	-22.41	0.000	-1.911951	-1.604443

According to the regression results in the above table, under the condition of significance level of 0.05, the P regression coefficient of the explanatory variables is -11.026003, which is negatively correlated; the regression coefficient of RW is 40.78012, which is significantly positively correlated; and the regression coefficients of D are 18.76396, which are positively correlated, respectively. The digital transformation of enterprises will have a certain impact on the level of industrial integration. That is, we can get a conclusion that the level of industrial integration plays a positive role in the process of enterprise digital transformation for green innovation technology.

According to the results in Table 8, the regression coefficient of industrial integration level is 0.0003832 with a P-value of 0.008 and a T-value of 2.65 at a significance level of 0.05, and the regression model further verifies the mediating utility played by the industrial integration level in the digital transformation to promote the green innovation technology.

5.6. Robustness Tests

Due to the limitations of the data itself, there may be errors in the conclusions of the study. After the regression analysis of the benchmark of green innovation technology affected by digital transformation, in order to prove its positive impact again and ensure the high reliability of the research conclusions, this part will replace the explanatory variables to enhance the reliability of the research conclusions, and eliminate special years to eliminate the endogeneity problems that may be brought by the sample selection for the robustness test.

5.6.1. Substitution of Explanatory Variables

The explanatory variable green innovation filings in the robustness test is replaced with green innovation efficiency (green innovation filings/innovation output), the ratio of the number of green licensed patents granted to listed companies plus one taken as a logarithm to the innovation investment of listed companies plus one taken as a logarithm to test the robustness of the benchmark regression in this paper.

The regression analysis is done on the basis of the test method and test model unchanged by replacing the changes. At the significance level of 0.05, it can be seen that the sign of the regression coefficients of robustness is consistent with the sign of the regression model, and the T-value and P-value are significant, passing the robustness test.

5.6.2. Excluding Special Years

In 2017, the State Intellectual Property Office changed the statistical standard of patent applications, and the statistical scope was changed from all patent applications received to only those that have been paid, so this paper considers excluding the relevant data in 2017.

According to the data in the table, it can be seen that by excluding the samples of special years, the regression coefficients of the explanatory variables basically coincide with the regression coefficients of the multivariate regression explanatory variables at the significance level of 0.05 , and the T-value and P-value are all significant, so that the baseline regression model of this paper passes the robustness test.

5.7. Heterogeneity Analysis

Considering that the unevenness and complexity of the sample's own resource endowment may lead to the variability of the impact of digital transformation on green innovation technology, this project will conduct a regression analysis of the effect of firms' digital transformation on green innovation technology based on regional differences.

Listed companies can be categorized into two groups based on their distribution regions: western and eastern regions. The effect of regional heterogeneity can be further analyzed through organization classification. According to the results it can be seen that among the 28,268 samples, 4,293 samples belong to the western region and 23,975 data belong to the eastern region, which can lead to a conclusion that there are more listed companies in the eastern region with digital transformation for green innovation technology than in the west.

Digital transformation and green innovation technology in the eastern region are positively correlated at the 0.05 level of significance, with strong correlation coefficients, and significant T-values and P-values; the correlation between digital transformation and green innovation technology in the western region is weak at the 0.05 level of significance, and the explanatory variable profitability is negatively correlated with the relationship of green innovation technology, and the T-values and P-values of the explanatory variables do not pass the significance. The results show that the digital transformation in the eastern region is more significant in enhancing its green innovation efficiency. The eastern region is the frontier of economy and science and technology, and plays an important role in the national science and technology strategy, undertaking the guidance of international advanced level. Listed enterprises in the east, in the field of gathering excellent talents, perfect hardware facilities, and favorable innovation environment, are more likely to empower their green innovation technology with digital transformation and enhance their green innovation efficiency compared with the western region where the news is closed. And the limited resource allocation in the west, in digital transformation at the same time undertake the goal of profitability and promote green innovation technology is not conducive to the enterprise's own current development.

6. Suggestions

This paper derives the topics from the literature analysis and utilizes empirical analysis and heterogeneity analysis to conduct a rational study of the topics, and now offers some comments and suggestions on the conclusions of this paper in the context of the socio-economic background.

6.1. Accelerating Digital Transformation

In the era of digital economy, enterprises should actively improve their digitalization level, continuously promote the process of enterprise digital transformation, take the initiative to incorporate green innovation into the digital collaboration system, and formulate effective measures to cope with the risks and challenges that may arise in the transformation process. Reasonable allocation of enterprise R & D investment and human resources investment, in the realization of economic goals, increase the investment in digital technology, encourage the enterprise staff to participate in the research and development and implementation of green innovation, and improve the efficiency of the implementation of green innovation research and development. Meanwhile, in the digital green innovation collaboration system, enterprises strengthen close ties with different stakeholders, unite departments upstream and downstream of the supply chain, improve their own level of industrial setup integration, share technology R&D information with each other, and jointly solve technical problems, enterprises can better promote the development of green innovation technology, understand and respond to social needs, cope with environmental protection pressures, and improve the enterprise's green innovation activities' efficiency and social influence of enterprises' green innovation activities.

6.2. Strengthening the Training of Innovative Talents

Innovative talents are the main force in the research and development of green innovative technologies, and are crucial to advancing the progress of innovative technology research and development in enterprises. As an important place to accommodate innovative talents, the cultivation of innovative talents is conducive to optimizing the industrial structure, promoting digital transformation and advancing the practice of green innovative technologies. Enterprises should moderately increase the proportion of science and innovation personnel according to the proportion of their own personnel structure, actively implement the industrial talent program, and continuously grow the enterprise high-level talent team; enterprises actively establish academician workstations, postdoctoral innovation practice bases, strengthen effective docking with universities around the world, promote the integration of industry, academia, research and application integration, and accelerate the cycle of accelerating the transformation of innovative thinking to the fruits of innovative technology; vigorously promote the scientists within the company We vigorously promote the spirit of scientists and craftsmen within the company, guiding and inspiring a large number of young research teams to invest in the practice of green innovation and technology in the enterprise.

6.3. Developing Differentiated Industrial Policies

According to the enterprise digital transformation of green innovation technology in the region, the impact of the development of differentiated industrial policy. From the point of view of industrial regional differentiation, in the eastern developed regions, should rely on the existing industrial advantages and basic advantages continue to enhance the level of economic development and openness to the outside world to continue to maintain the good trend of digital transformation, promote green technology research and development and application, guide the traditional industries to high-end, intelligent, green transformation, while cultivating new industries, the formation of green innovation industry clusters. In the less developed regions in the west, the quality of the labor force is improved to provide talent protection for the digital transformation of enterprises; through policy preferences and resource allocation, green innovative enterprises are attracted to settle in the region, driving the development of the regional green economy. From the point of view of industrial sector differentiation, enterprises in the manufacturing industry should be encouraged to adopt the Internet of Things, big data and other technologies to improve production efficiency and quality; guide enterprises to build a green supply chain system to reduce energy consumption and emissions in the product life cycle.

6.4. Strengthening Synergistic Cooperation and Improving the Level of Industrial Integration

Collaboration includes cross-regional and cross-industry cooperation. Cross-regional cooperation has gradually become the key to digital transformation, with enterprises, technology companies and research institutions taking major projects such as "East Counts, West Counts" as the starting point to optimize the spatial distribution of enterprises and carry out in-depth cooperation based on their respective strengths, so as to promote technological innovation and business model innovation. Cross-industry cooperation is conducive to the realization of complementary strengths among industries in different regions and the deep integration of digital technologies with various industrial sectors. Therefore, to promote digital transformation and the development of green innovative technologies, efforts should be made to strengthen the integration of different industries, accelerate the cultivation of a unified data market, break down the information barriers between industries, promote the free flow of data elements, strengthen synergies and cooperation between different industries, and better maintain the linkage of development.

Through the use of digital technology to realize real-time, transparent and shared data and information, enterprises can reduce information technology barriers, establish an intelligent supply chain management system, realize the whole process of product life cycle management, optimize the allocation of resources, gain a better insight into the market demand, improve the efficiency of environmental governance, develop green products and solutions, and play a role in enhancing the efficiency of green innovation and the sustainable development ability of enterprises. Green Innovation Value.

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