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Research on the Impact of Digital Economy on Green Technology Innovation Under the Goal of "Gual Carbon"

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Abstract

From the perspective of input and output, indicators were constructed to measure the green technology innovation and digital economy development capabilities of 244 prefecture-level cities in China from 2010 to 2019. The spatial Durbin model was used to analyze the relationship between the two, as well as the impact factors of barrier degree, urban geographic location and population size heterogeneity. Finally, suggestions were put forward based on the actual urban development. The results show that: (1) The Moran's I of green technology innovation in 244 cities in China from 2010 to 2019 mainly clustered in the first and third quadrants, with local spatial clustering. When the development of digital economy increases by 1%, green technology innovation will increase by 0.268%, and the related indicators of early investment are at the forefront of the impact of obstacle degree. (2) From the perspective of utility decomposition, the impact of digital economy on green technology innovation is mainly concentrated in the direct effect, the promotion effect of neighboring areas on local is not significant, and the overall effect has a time lag; (3) From the perspective of geographical location, its promotion effect exists only in the eastern region. From the perspective of different urban population sizes, its promoting effect exists in both megacities and big cities.

Keywords: The goal of "Gual Carbon", Digital Economy, Green Technology Innovation, SDM Model

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1. Introduction

The digital economy, driven by the new generation of information technology, has increasingly emerged as a pivotal catalyst for promoting economic development (Chen et al., 2022). In China, the digital economy has witnessed steady expansion. According to the "China Digital Economy Development Research Report" published by the China Academy of Information and Communications Technology in 2023, it is projected that China's digital economy will reach a scale of 50.2 trillion yuan in 2022, accounting for approximately 41.5% of GDP. The development of the digital economy is becoming a crucial factor for the high-end, intelligent, and sustainable development of the real economy. To promote green development in line with the "dual carbon" goal, it is imperative to expedite research, development, and promotion of advanced technologies for energy conservation and carbon reduction. Enhancing innovation capacity in green technology has become an urgent necessity. In recent years, numerous scholars have examined the impact of innovation capacity in green technology on economic development. The digital economy constitutes a significant aspect of economic progress. Multiple scholars have substantiated that green technology innovation exerts a positive influence on the digital economy's advancement. Consequently, what role does the spatial perspective play in fostering green technology innovation through digital economy? Simultaneously, after proposing the "dual carbon" goal and implementing China's dual control system for total carbon emissions and intensity, attention should be given to maximizing the effect of the digital economy on promoting green technology innovation.

The rapid rise of digital economy has triggered revolutionary changes in the economic field. As the main driving force of national competitive advantage in the information age (Wei and Hou, 2022), digital economy has received wide attention from all walks of life. At present, the research on digital economy has been widely carried out from various aspects, including the definition of concepts, the establishment of measurement indicators and economic and social benefits. Specifically, from its economic and social benefits, the development of digital economy and green economy has attracted much attention as a realistic development plan to solve the current environmental problems. Some scholars believe that digital economy and economic greening present an inverted U-shaped relationship, and "energy rebound effect" is the main reason for the "inverted U-shaped" constraint (Fan and Xu, 2021). Some scholars believe that through the three intermediary variables of green technology innovation, industrial structure rationalization and upgrading, digital economy effectively promotes the development of green economy (Hao et al., 2023). From the basic concept of the digital economy, it is not difficult to see that it is a melting pot of information technology and the Internet, which brings huge innovation potential into multiple fields of green economic development. First, in terms of energy efficiency improvement, the digital economy achieves efficient management of energy systems through technologies such as intelligence, automation and data analysis (Xu et al., 2022; Zhang et al., 2022).

Second, in terms of the integration of renewable energy, the renewable energy system can better coordinate with the power grid through digital technology to ensure the stability of energy supply, but some scholars believe that the income effect caused by the digital economy and the high dependence on electricity consumption will lead to energy rebound (Fan and Xu, 2021). Third, in terms of energy conservation and clean technology innovation, big data analytics, simulation modeling, and virtual reality technologies can be used to design and test new green solutions, thereby speeding up technological innovation and reducing actual trial costs. The above statement shows that data-driven digital economy is affecting the level of innovation in different regions (Xu and Qiu, 2022; Li et al., 2021), and green technology innovation, as a kind of innovation, is also gradually changing the development model of digital economy.

As the driving force behind the development of green economy (Wang and Ren, 2022; Wang et al., 2022), green technology innovation has also been studied by a wide range of scholars. Scholars' research on green technology innovation from the urban perspective covers many aspects, including renewable energy technology development (Dong et al., 2022), enterprise performance improvement (Su and Li, 2021; Li et al., 2017), carbon capture and emission reduction (Lin and Ma, 2022; Cheng and Yang, 2023), green building and urban planning (Shao et al., 2022), policy and legal framework (Wang et al., 2022; Shen et al., 2021), and socio-economic impact (Yu et al., 2020). These studies aim to promote sustainable development, reduce environmental pressures and achieve efficient use of resources, while also taking into account concerns for social equity and economic sustainability to meet the energy and resource needs of future generations and address global challenges such as climate change.

As for the impact of digital economy on green technology innovation, it is believed that enterprise digitalization mainly promotes enterprise green technology innovation by improving enterprise information sharing level and knowledge integration ability (Song et al., 2022)[20]. Tang C et al believe that the construction of digital infrastructure promotes the diffusion and progress of green technology and influences the innovation of green technology (Tang et al., 2021). Cheng Guangbin et al believe that digital economy affects high-quality development by influencing the level of green technology innovation (Cheng et al., 2022). In terms of the impact of green technology innovation on digital economy, digital economy can significantly improve the efficiency of urban green economy by influencing technological innovation, and has a positive spatial spillover effect (Zhu and Li, 2023). In addition, Zhang M and Liu Y et al. analyzed the synergistic relationship between digital economy and green technology innovation, and found that the synergistic effect of the two has different carbon emission reduction effects on local and foreign areas (Zhang and Liu, 2022).

In the above research on the impact of digital economy on green technology innovation, the first is the lack of setting standards for green technology innovation indicators. At present, there are three kinds of green technology innovation index system. First, based on the construction index of the number of patent applications, Chen Zhe et al. (Chen and Zheng, 2022) used the number of patent applications as the main variable to measure the development of green technology to study its relationship with high-quality economic development. Second, to construct an index of the relationship between the number of patent applications, Qi Shaozhou et al. (Qi et al., 2018) used the ratio of the number of green patents applied by listed companies to the total number of patent applications and the ratio of the number of green invention patents to the total number of invention patent applications to study the green technology innovation in manufacturing industry. Thirdly, construct the index system from the Angle of cost and benefit. For example, Wang Xu et al. (Wang and Chu, 2019), based on considering innovation efficiency, adopted the Super-SBMc model containing unexpected output to measure from the perspective of cost. Sun Yanming et al. (Sun et al., 2021) constructed green technology innovation indicators with innovation benefits and environmental costs from the perspective of input and output. From the above indicator construction methods, the index construction of green technology innovation is mainly based on the number of patent applications and authorization, the construction method is too simple, and the overall control of the early investment and the landing of the later innovative technology is lacking. Secondly, the research on the correlation between the two focuses on the provincial perspective, and there are few studies on the measurement criteria of cities and different urban agglomerations from the spatial perspective. Based on the above problems, this paper constructs digital economy and green technology innovation capability indicators based on the data of 244 cities in China respectively to explore the impact of digital economy on green technology innovation, decomposes the effect of digital economy through the spatial Durbin model, and measures the promotion of digital economy on green technology innovation under regional heterogeneity and city size heterogeneity. Finally, according to the obstacle degree model, which factors have the greatest impact in the digital economy are measured and policy recommendations are put forward according to the above results.

2. Research design

2.1 Theoretical analysis and research hypothesis

At present, data has become one of the development factors, and the application of data will have a profound impact on green technology innovation. First, the digital economy, through the collection, analysis and utilization of big data, can help the green technology sector better understand environmental issues and energy use. This data-driven innovation allows researchers and engineers to more accurately evaluate problems, discover solutions, and conduct simulations and predictions that accelerate the development of green technologies. Second, digital technologies such as the Internet of Things (IoT) and sensor technology make monitoring of environmental and energy systems more intelligent and refined, which helps reduce waste and improve efficiency, and drives the integration and application of renewable energy. Third, the digital economy offers a wide range of online education and collaboration opportunities for green technology innovation. People can learn the latest green technology knowledge through the network and accelerate talent training. At the same time, cooperation on a global scale has become easier, and experts can collaborate remotely to solve problems and promote technology exchange and sharing. Sharing research results at a lower cost can help reduce trial costs and speed up innovation cycles by creating virtual models to simulate and test various development scenarios for green technology innovations. Fourth, the low-cost nature of the digital economy provides more funds and investment channels for green technology innovation, and the faster and easier flow of funds helps attract investors to invest in the research and development and promotion of green technology. Based on the above analysis, the hypothesis that the development of digital economy can significantly improve the innovation ability of urban green technology is put forward.

2.2 Research design

2.2.1 Model setting

In order to explore the impact of digital economy development on green technology innovation, the benchmark regression equation is constructed as follows:

$$ln\,GT_{it} = ln\,\alpha + \beta\,ln\,DEI_{it} + \gamma\,ln\,Control_{it} + \mu_i + v_t + \varepsilon_{it} \qquad (1)$$

In formula (1), GT_{it} represents the green technology innovation capability of region i in year t, DEI_{it} represents the digital economic development index of region t in year t, $Control_{it}$ is a set of control variables of region i in year t. The control variables include population density (P), level of economic development (A), industrial structure (IS_2), level of urbanization (URB), percentage of loan balance to GDP (PLB), and year-end savings balance of urban and rural residents (YSB).

2.3 Description of variables

Green technology innovation: Referring to the practice of Su Yuan (Su and Li, 2021), this paper establishes the index foothold from the input and output of green innovation, and establishes a comprehensive index by adding the scale of green enterprises. Green innovation input takes R&D investment and the number of R&D personnel as the tertiary indicators, and green innovation output takes the number of green patent applications and the total output value of green industry-related listed companies as the tertiary indicators. For the specific index system, refer to Table 1 below.

Table 1: Establishment of green technology innovation index

Primary index	Secondary index	Three-level index	Unit	Index attribute
Green technology innovation ability	Green enterprise scale	Number of listed companies related to green industry	Unit	Positive index
	Initial Investment	R&D investment	CNY 10,000 yuan	Positive index
		Number of R&D personnel	Person	Positive index
	Actual output	Number of green patent applications	Unit	Positive index
		Total output value of listed companies related to green industry	CNY 10,000 yuan	Positive index

From the analysis of investment in green technology innovation, due to the long transformation cycle of green technology innovation achievements, it needs a lot of capital and personnel investment. More R&D investment funds and personnel usually represent that the society or enterprise is willing to allocate more resources for innovation activities, more resources to support technology experimentation, prototype development and product testing, so as to improve the probability of transformation of innovation results. From the analysis of green technology innovation output, most scholars use green patent output and other indicators to measure output capacity, and green patent application directly represents the transformation of innovation achievements of enterprises. The results of green technology innovation reflected in the social level are reflected in the profits brought by green innovation. Since there is no corresponding classification of green industry in the national economic industry, this paper adopts the data of listed companies as a substitute. According to the segmentation of green industry in the Green Industry Guidance Catalog (2019), the listed companies related to green industry were screened in the flush software, and 32 concept blocks were selected; there are 3,040 listed companies in 32 sectors. Among these companies, 860 companies are selected for those whose main business includes green industry-related businesses, whose main products include green industry-related products, and whose main business income accounts for more than 20% of green industry-related income. After determining the name of the company, it is matched in CSMAR database according to the securities code, and the research and development investment amount, the number of research and development personnel and the total output value of the company are screened. In addition, the number of green patent applications comes from the State Intellectual Property Office, which is matched using WIPO's Green List of International Patent Classifications.

Digital economy: The establishment of digital economy indicators needs to be considered in many aspects. This paper builds digital economy development indicators by referring to the Internet comprehensive development index constructed by Huang Qunhui et al. (Huang et al., 2019). Considering the infrastructure and personnel input of the digital economy, the proportion of Internet broadband access users per 100 people and computer software and software industry employees is selected as the representative. Second, the total number of telecommunications services per capita represents the output related to the digital economy. Finally, in order to reflect the actual number of participants in the digital economy, the number of mobile phone users per 100 people and the number of international Internet users are selected as representatives. Specific values are obtained after indexes are processed by entropy weight method. Specific indexes are shown in Table 2 below.

Table 2: Digital economy indicators

Indicator	Variable Selection	Variable Explanation	Unit	Index attribute
Digital Economic Development	Initial Investment	Internet broadband access users per hundred people	households/ hundred people	Positive index
	Related Output	Proportion of computer software and software industry employees	%	Positive index
		Per capita total amount of telecommunications services	yuan/person	Positive index
	Active Users	Number of domestic mobile phone users per hundred people	households/ hundred people	Positive index
		International Internet phone users	households	Positive index

Control variables: The main influencing factors on green technology innovation are selected according to previous literature studies, and population size, economic development level, industrial structure and urbanization level are the main control variables. The specific classification is shown in Table 3 below.

Population size (P): The population in different areas will have diverse impacts on the ecosystem. On the one hand, the population concentration will create more market demand and promote the development and application of green technology. Cities with large populations face more environmental challenges, inspiring green technology innovation to find solutions to improve environmental conditions. The regression coefficient of expected population size for green technology innovation is positive.

Level of economic development (A): Developed regions have richer R&D resources and technical personnel, and invest a lot of money in green technology research and development to promote the speed and quality of innovation. There is greater demand in these regions and the need for environmentally friendly and sustainable solutions is driving companies to innovate. At the same time, developed regions are able to introduce and apply new technologies more quickly, and policy support provides the finance and environment for green technology innovation to support its role in sustainable development. Therefore, this paper chooses per capita GDP to measure the level of urban economic development, and converts the annual nominal GDP into the real GDP based on 2010 to eliminate the impact of price changes. At present, China is still a developing country, and the regression coefficient of green technology innovation at the development level is expected to be positive.

Industrial structure (IS_2): The secondary industry plays an important role in green technology innovation, which both faces environmental pressures and brings innovation opportunities. The industrial sector is often associated with resource waste and environmental pollution, so green technologies need to be sought to reduce environmental impact. Green technology innovation drives industrial transformation, requires more efficient and environmentally friendly production technologies, and can bring market opportunities, competitive advantages and sustainable development to enterprises. Policy support and technological impetus can accelerate the green transformation of the secondary industry, thus achieving more sustainable industrial development while balancing economic growth with environmental protection needs. At present, China is still in the transition period of high-quality development, so this paper chooses the proportion of added value of the secondary industry to GDP to represent the industrial structure, and the regression coefficient of industrial structure for green technology innovation is expected to be negative.

The level of urbanization (URB): As urbanization continues to accelerate, the level of urbanization affects population distribution, resource use, and environmental stress. Areas with high levels of urbanization face more environmental challenges such as energy consumption, waste generation and air pollution. However, urbanization also presents opportunities for green technology innovation. The increase in city size and demand has spurred the demand for environmentally friendly solutions and sustainable development, prompting cities to explore more efficient transportation systems, clean energy and smart city facilities. Regions with a higher degree of urbanization usually have more scientific research institutions, innovative enterprises and human resources, which provides a favorable environment for the development and application of green technologies. The measurement of urbanization level generally has two dimensions: population urbanization and land urbanization. Because the number of non-agricultural population in China's Urban Statistical Yearbook has stopped being released since 2019, population urbanization index cannot be obtained. This paper uses land urbanization index to measure, that is, the proportion of urban construction land in the urban area, and the regression coefficient is expected to be positive.

Percentage of outstanding loans to GDP (PLB): A higher ratio of outstanding loans to GDP indicates a more convenient financing environment, which can help to finance green technology innovation, and may indicate the level of national attention to innovation. However, a high proportion may also be accompanied by a concentration of risks, which may affect economic stability and thus innovation investment. In addition, the high proportion can also reflect the market demand for green technology and the government's ability to guide financial institutions through policies to support green technology innovation. Therefore, in terms of promoting green technology innovation, the financing environment is represented by dividing the balance of loans of financial institutions by GDP at the end of the year, and the expected regression coefficient is positive.

Year-End Savings Balance of Urban and Rural Residents (YSB): High levels of savings help finance investment and promote the participation of individuals, entrepreneurs, and small businesses in the development and application of green technologies, while increasing incentives for innovation. In addition, a large number of residents have enough savings to support green technology products, guiding the market to meet demand and thus promoting green technology innovation, so the expected regression coefficient is positive.

Table 3: Main Variables in the Regression Equation

Variable Types	**Variable Names**	**Variable Units**	**Variable Explanations**
Dependent Variable	Green Technology Innovation Capacity (GT)	None	Urban Green Technology Innovation Capacity
Independent Variable	Digital Economic Development Index (DEI)	None	Urban Digital Economic Development Index
Control Variable	Population Size (P)	Per Ten Thousand People	Year-End Total Population
	Level of Economic Development (A)	CNY Yuan	Per Capita Gross Regional Product (GRP)
	Industrial Structure (IS_2)	%	Proportion of Added Value of the Secondary Industry to GDP
	Level of Urbanization (URB)	%	Proportion of Urban Construction Land to Urban Area
	Percentage of Loans to GDP (PLB)	%	Year-End Proportion of Outstanding Loans by Financial Institutions to GDP
	Year-End Savings Balance of Urban and Rural Residents (YSB)	CNY: Ten Thousand Yuan	Year-End Savings Balance of Urban and Rural Residents

2.3.1 Data preprocessing

In this paper, entropy weight method is applied to both green technology innovation and digital economy indicators. Firstly, data is standardized, and positive and negative indicators are standardized respectively.

For positive indicators：

$$X_{ij}^{'} = (X_{ij} - minx_i)/(maxx_i - minx_i) \tag{2}$$

In formula (2), $X_{ij}^{'}$ is the standardized value of the indicator X_{ij} ，$X_{ij}$is the original value of the *j* positive indicator for the i sample，$minx_i$ is the minimum value of all positive indicators for the i sample，$maxx_i$ is the maximum value of all positive indicators for the i sample.

For negative indicators：

$$X_{ij}^{'} = (maxx_{ij} - X_j)/(maxx_j - minx_j) \tag{3}$$

In formula (3), the interpretation of the indicators is similar to that in Equation 2.

In order to avoid the nonsense caused by zero value of data, the whole data translation of the dimensionless data is carried out, that is, $X_{ij}^{'} = X_{ij} + \alpha$. In order to minimize the impact of data translation on the original data, the value α in this paper is 0.00001.

(1) Calculate index weight:

$$Y_{ij} = X_{ij}^{'}/\sum_{i=1}^{n} X_{ij}^{'} \tag{4}$$

(2) Entropy calculation:

$$e_j = -\frac{1}{lnn}\sum_{i=1}^{n}(Y_{ij} * lnY_{ij}) \tag{5}$$

(3) Calculation of information entropy redundancy:

$$d_j = 1 - e_j \tag{6}$$

(4) Index weight calculation:

$$\omega_i = d_j/\sum_{j}^{m} d_j \tag{7}$$

In formula (4), (5), (6), (7), Y_{ij} is index weigh; n represents the product of the total number of years and the number of indicators, m represents the number of indicators; e_j represents the entropy value; ω_i represents the weights of the indicators.

2.3.2 Data source

The green technology innovation data is mainly from the Royal Flower financial network, CSMAR database, the State Intellectual Property Office, and the green patent classification number is from the WIPO Green Patent List. Digital economy data and other control variables are mainly derived from the Chinese Urban Statistical Yearbook.

3. Empirical results and analysis

3.1 Correlation test

In order to prove the spatial correlation of the explained variables, this paper conducts a correlation test for green technology innovation at the city level. Common Spatial autocorrelation tests include Moran's I test, Geary's C test, Local Indicators of Spatial Association (LISA), Getis-Ord Gi test in order to understand the global spatial autocorrelation of the whole and minimize the influence of outliers, Moran's I test is selected. When the range of Moran's I is (0,1), it is considered that there is a positive spatial autocorrelation, and when the range of Moran's I is (-1,0), it is considered that there is a negative spatial correlation. The original hypothesis is that there is no spatial autocorrelation of geographical data, and the alternative hypothesis is that there is spatial autocorrelation of geographical data. Moran's I is calculated as follows:

$$Moran's\ I = \sum_{i=1}^{N}\sum_{j=1}^{N}\omega_{ij}(x_i-\bar{x})\left(x_j-\bar{x}\right)/\sum_{i=1}^{N}\sum_{j=1}^{N}\omega_{ij}\sum_{i=1}^{N}(x_i-\bar{x})^2 \quad (8)$$

In formula (8), x_i 、x_j are the green technology innovation capability index of cities i and j respectively, and $\bar{x}$ is the average of the green technology innovation capability index of all cities. ω_{ij} is the spatial geographic weight matrix after row standardization, and common ones include 0-1 adjacency matrix, geographical distance weight matrix, economic distance weight matrix, and economic geography nested matrix. In order to explore the spillover effect of digital economy on green technology innovation, this paper selects the inverse distance square matrix with better effect after several regressions and tests, and the calculation expression is as follows:

$$W_{ij} = 1/d_{ij}^2(i \neq j) \quad (9)$$

In formula (9), d_{ij} represents the distance between geographical units i and j, obtained by the latitude and longitude between them. The weight value shows that the closer the distance between two places, the larger the value, and the farther the distance, the smaller the value.

Based on the data of green technology innovation ability of 244 cities in China from 2010 to 2019, Moran's I from 2010 to 2019 was obtained by Stata17 software, as shown in Table 4 below.

Table 4: Moran's I for Overall Green Technology Innovation in Chinese Cities

Year	2010	2011	2012	2013	2014
Moran's I	0.061**	0.104***	0.118***	0.133***	0.102***
Year	2015	2016	2017	2018	2019
Moran's I	0.099***	0.103***	0.115***	0.123***	0.103***

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively, based on the significance test. The same applies to the asterisks in the rest of the text and will not be reiterated here.

From the results in the table, it can be seen that the green technology innovation of 244 cities in 2011-2019 showed significant at 99% confidence level, the Moran's I in 2010 was significant at 95% confidence level, and the Moran's I in 10 years was greater than 0, indicating that carbon dioxide showed a positive spatial correlation in all places. In order to better see the interregional green technology innovation aggregation, this paper draws the local Moran's I scatter plot of green technology innovation in 2019, as shown in Figure 2. The Moran's I is mainly distributed in the first and third quadrants, indicating that China's green technology innovation currently has a significant local spatial aggregation feature in geographical space. In addition, it mainly presents high-high agglomeration and low-low agglomeration. It can be seen from the results in the table that from 2011 to 2019, the green technology innovation of 244 cities is significant at 99% confidence level, the Moran's I in 2010 is significant at 95% confidence level, and the Moran's I in 10 years is greater than 0. It means that carbon dioxide shows a positive spatial correlation in different places. In order to better see the interregional green technology innovation aggregation, this paper draws the local Moran's I scatter plot of green technology innovation in 2019, as shown in Figure 1. The Moran's I is mainly distributed in the first and third quadrants, indicating that China's green technology innovation currently has a significant local spatial aggregation feature in geographical space. And it mainly presents high-high agglomeration and low-low agglomeration.

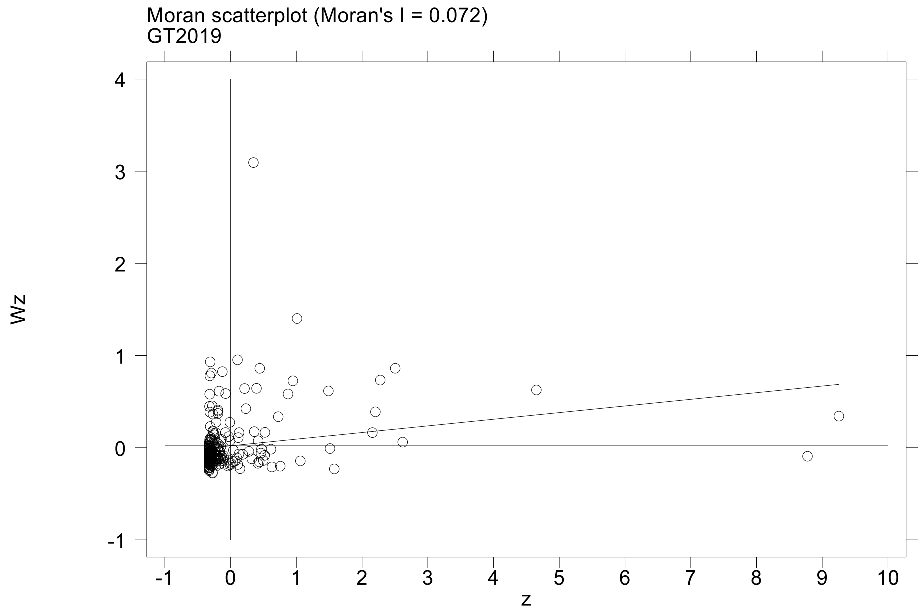

Figure 1: Moran's I Scatter Plot（Year 2019）

3.2 Selection and testing of spatial metrology model

As shown in Table 5, VIF test was carried out on the sample data, and the results were as follows. It was found that the VIF value of each variable was less than 10, the highest value was 8.86, the lowest value was 1.44, and the average value was 3.61, indicating that there was no serious multicollinearity between the variables.

Table 5: Collinearity Test

Variable name	VIF	1/VIF
lnYSB	8.86	0.113
lnP	4.71	0.212
lnA	4.03	0.248
lnDEI	2.72	0.368
lnPLB	2.02	0.495
$lnIS_2$	1.52	0.659
lnURB	1.44	0.696
Mean VIF	3.61	

As can be seen from the above analysis, green technology innovation among 244 cities has spatial correlation, so the spatial weight matrix should be added to the model, and the empirical part should be estimated by using a spatial econometric model to make the model fit better. In this paper, OLS regression and LM test are performed first, and the test results are shown in Table 6 below. The results show that P-values under LM test and Robust LM test are significant at different confidence levels, indicating the existence of spatial error effect and spatial lag effect. Mixed panel regression is rejected, and the spatial Durbin model is selected for preliminary judgment. After that, Hausman Test was used to determine the adoption of fixed effects model or random effects model. According to the test results in Table 7, the null hypothesis "the difference between coefficients is not systematic" was rejected and the fixed effects model was adopted.

LR test and Wald test were used to determine whether the spatial Durbin model could be degenerated into SAR and SEM models. In other words, the applicability of the spatial Durbin model was further verified on the premise of determining the spatial correlation between variables. The results were shown in Table 7, both LR test and Wald test passed 99% significance. SDM cannot be degraded into SEM model and SAR model. Based on the above tests, this paper chooses to use SDM model for subsequent empirical analysis.

Table 6: Non-Spatial Panel Data Estimation and LM Test Results

Variable Name	Regression Coefficient	p-value
lnDEI	0.166***	0.008
lnP	0.778***	0.000
lnA	0.966***	0.000
$lnIS_2$	1.286***	0.000
lnURB	0.192***	0.000
lnYSB	0.723***	0.000
Test Method	Statistical Value	p-value
LM test no spatial error	17.774***	0.000
Robust LM test no spatial error	3.749*	0.053
LM test no spatial lag	17.634***	0.000
Robust LM test no spatial lag	3.609*	0.057

Table 7: Hausman Test, Wald Test and LR Test Results

Test Method	Statistical Value	p-value
LR Lag	171.06***	0.000
LR Err	113.72***	0.000
Wald Lag	9.3e+10***	0.000
Wald Err	114.17***	0.000
Hausman	48.00***	0.000

3.3 Estimation results and analysis of spatial Durbin model

3.3.1 Result analysis of spatial Durbin model

Based on the results of the above correlation tests, it can be seen that this paper should adopt the fixed effect spatial Durbin model for spatial econometric regression. In order to explore the degree of fit between various models, this paper uses SDM model regression to compare the regression results of static panel model and dynamic panel, and the regression results of the four models are shown in Table 8 below.

Table 8: Estimation Results of Different Panel Models

Variable Name	OLS	FE	GMM	SDM
lnDEI	0.166*** (2.66)	-0.125*** (-3.64)	0.103 (0.48)	0.268*** (3.61)
lnURB	0.192*** (5.01)	-0.024 (-0.61)	-0.250 (-1.32)	0.154*** (4.64)
lnPLB	0.830*** (10.48)	0.091 (0.93)	2.963*** (4.02)	0.663*** (7.89)
lnYSB	0.723*** (8.16)	0.102 (1.13)	-3.784*** (-3.63)	0.883*** (8.99)
lnP	0.778*** (8.12)	0.508 (1.50)	6.117*** (4.87)	0.440*** (4.25)
lnA	0.966*** (11.39)	1.084*** (5.08)	5.513*** (4.73)	1.198*** (12.18)
$lnIS_2$	1.286*** (9.09)	0.361* (1.72)	2.712** (2.40)	-0.191 (-1.19)
Constant Term	-29.521*** (-32.91)	-13.386*** (-5.54)	-40.293*** (-6.08)	—
ρ	—	—	—	0.403*** (8.53)
sigma2_e	—	—	—	1.568*** (34.68)
Sample Size	2440	2440	2196	2440
R-squared	0.612	0.516	—	0.638

From the model fit degree of the four models in the above table, the R-squared value of SDM is 0.638, which means that the SDM model has the highest goodness of fit for the relationship between variables. In addition, the spatial autocorrelation coefficient ρ passed the significance test at 99% confidence level, with a value of 0.403, indicating that there is a positive spatial spillover effect of green technology innovation, that is, the enhancement of the green technology innovation capability of the city will lead to the enhancement of the green technology innovation capability of the surrounding area. The reasons for the positive spatial spillover effect may stem from the following points: First, cities play the role of innovation and knowledge aggregation, promoting the cross-domain knowledge exchange and sharing of green technologies. This knowledge sharing not only accelerates the spread of green technologies, but also inspires innovators in other cities to step into similar fields of innovation. Secondly, the cooperative atmosphere and network of the city create a favorable environment for the positive spatial spillover effect. Innovation in green technology often requires the blending of expertise from different fields, and partnerships between companies, research institutions and universities in cities can promote the blending and sharing of knowledge, thus burning the spark of innovation even brighter. In addition, policy support and resource investment in cities also provide a solid foundation for green technology innovation. Government departments often create incentives to encourage the development and application of green technologies, which provides innovators with the opportunity to realize their ideas. At the same time, the rich infrastructure, capital and talent pool within the city provides the necessary resource support for innovation.

The estimated results of digital economy, the core explanatory variable selected in this paper, in the four models are 0.166, -0.125, 0.103 and 0.268 respectively, and most of the results are positive, among which the regression coefficients of panel mixed regression, fixed effect regression and SDM model all pass the significance test of 1%. It shows that there is a significant positive correlation between green technology innovation and digital economy. From the perspective of the four models respectively, because static panel regression does not consider the spillover effect between regions, the explanatory effect of digital economy on green technology innovation is smaller than the regression value of the spatial Durbin model, which is 0.166. The GMM model takes the digital economy as an endogenous variable and the green technology innovation index, which lags one stage, as an exogenous variable, making the explanatory effect of the digital economy on green technology innovation become 0.103. Therefore, the regression coefficient of green technology innovation estimated by the SDM model adopted in this paper is more accurate, with a value of 0.268, that is, when the development of digital economy increases by 1%, the green technology innovation ability increases by 0.268%.

From the perspective of control variables, population size, economic development level, the proportion of loan balance to GDP, the balance of urban and rural residents' savings at the end of the year, and the level of urbanization passed the significance test of 1%. (1) The regression coefficient of population size is 1.198, indicating that there is a significant positive correlation between population size and green technology innovation, that is, the increase of population size will promote the increase of green technology innovation. (2) The regression coefficient of economic development level is 0.440, indicating that there is a significant positive correlation between economic development level and green technology innovation, that is, the increase of per capita GDP will promote the increase of green technology innovation. (3) The regression coefficient of urbanization level is 0.154, indicating a significant positive correlation between urbanization level and green technology innovation, that is, the improvement of urbanization level will promote the improvement of green technology innovation ability. The rapid expansion of cities will lead to changes in land use in surrounding areas. For example, agricultural land will be transformed into industrial land. Industrial pollution will put more environmental pressure on cities and promote the increase of green technology innovation. (4) The regression coefficient of the ratio of loan balance to GDP is 0.663, indicating that the ratio of loan balance to GDP is positively correlated with green technology innovation, that is, the improvement of loan intensity will promote the improvement of green technology innovation capability. Because green technology innovation has a low degree of transformation of its own achievements, it has a large degree of dependence on funds. A more active lending environment will help solve the worries of green technology innovation. (5) The regression coefficient of urban and rural residents' savings balance at the end of the year is 0.883, indicating that urban and rural residents' savings will show a positive correlation with green technology innovation, and the wealth accumulation of urban residents lays the foundation for residents' investment in green technology innovation.

3.3.2 Spatial Durbin model decomposition of direct effects and indirect effects

Through the decomposition of the above model, Table 9 specifically gives the direct effects, indirect effects and total effect values decomposed by the model regression results. For the core explanatory variables, the direct effect of digital economy is 0.274, and the indirect effect is 0.277. The direct effect passes the significance test of 1%, while the indirect effect is not significant. The result shows that the promotion of local digital economy has a relatively obvious positive effect on local green technology innovation. The total effect of digital economy is 0.552, which is in the same direction as the decomposed direct effect and indirect effect, and the effect is larger. The reason why the indirect effect is not significant may be that the development of China's digital economy is still in the key period, and the development of digital economy in various places is still dominated by local enterprises and supported by local governments. The lag in the development of trans-regional digital economy leads to the improvement of green technology innovation mainly from the local. In addition, the larger the total effect, the greater the digital economy development of enterprises in one place will promote green technology innovation in the local and surrounding areas. Therefore, it is necessary to encourage the coordinated development of cities, share basic costs and risks in the development of digital economy, and commit to win-win cooperation.

Table 9: Decomposition of Spatial Spillover Effects in the Digital Economy

Variable Name	Direct Effect	Indirect Effect	Total Effect
lnDEI	0.274*** (3.67)	0.277 (0.85)	0.552* (1.73)
lnURB	0.142*** (4.54)	-0.669*** (-3.44)	-0.527*** (-2.76)
lnPLB	0.681*** (8.56)	0.671* (1.71)	1.352*** (3.55)
lnYSB	0.862*** (9.38)	-0.967** (-2.13)	-0.105 (-0.24)
lnP	0.475*** (4.89)	1.914*** (3.97)	2.389*** (5.15)
lnA	1.212*** (12.89)	0.549 (1.21)	1.760*** (4.03)
$lnIS_2$	-0.100 (-0.61)	5.512*** (8.06)	5.412*** (8.14)

Among the control variables, the direct effect of population size (P) was 0.475 and the indirect effect was 1.914, both of which passed the 1% significance test. That is, an increase in the size of the local and neighboring population will significantly increase the amount of green technology innovation in the region. The indirect effect is larger than the direct effect. The reason may be that the larger population size may mean more market demand and potential innovators, but the direct effect on green technology innovation may be relatively small due to the lack of relevant infrastructure, talents and resources at the initial stage. The regional innovation ecosystem that has been formed in the surrounding area provides effective support for the formation of local green technology innovation.

The direct effect of economic development level (A) is 1.212, that is, the growth of per capita GDP in the region will significantly improve the level of green technology innovation in the region. The indirect effect of economic development level is 0.549, and the result is not significant. The reason may be that the research and development cycle of green technology innovation is long, and the local economic development level represents a larger number of potential users and consumers, encouraging local enterprises to carry out green technology innovation to meet the market demand. At the same time, the local GDP level usually determines the local available resources, including talent, capital, facilities and so on. A higher local GDP may mean that more investment and resources are available for green technology innovation, while the resources of neighboring countries may be more inclined to be used for their own development, thus limiting their impact on local green technology innovation.

The direct and indirect effects of urbanization level (URB) were 0.142 and -0.669, respectively, which passed the significance test. The different sign of regression coefficient indicates that the improvement of local urbanization level will increase the level of green technology innovation, and the improvement of neighboring urbanization level will decrease the level of green technology innovation. First, the increase of urban construction land will bring more challenges to the ecological environment, and cities will increase their local investment in green technology innovation whether for their own development or due to environmental requirements, thus promoting their development. However, the effect of the improvement of the level of urbanization in other places is to inhibit the local green technology innovation, which may be attributed to the management idea that each region is limited to "one mu and three points of land" after being divided according to the norms of administrative regions.

The direct effect and indirect effect of the percentage of loan balance to GDP (PLB) are 0.681 and 0.671, respectively, which pass the significance test of 99% and 90% respectively, both of which show the positive impact of the percentage of loan balance to GDP on green technology innovation. This is as expected, showing the importance of social funding activity for green technology innovation. The situation is different when looking at capital activity from the perspective of urban residents. The direct effect and indirect effect of the YSB are different, with a value of 0.862 and -0.967, and pass the significance test of 99% and 95% respectively. This means that the savings balance of local urban and rural residents at the end of the year promotes the local green technology innovation, but the savings balance of rural and urban residents in other places inhibits the local green technology innovation. This may be because the inflow of foreign savings mostly flows into the local innovation and development process, and enterprises with insufficient access to local capital are hindered in seeking external financial support, thus producing inhibitive effect.

3.3.3 The impact of digital economy on green technology innovation under regional heterogeneity

The previous article has analyzed the impact of digital economy on green technology innovation among 244 cities. China's vast geographical area may have different impacts on different regional classifications. Therefore, according to the division of the eastern and western regions by the Bureau of Statistics of China, the eastern region includes 84 cities such as Beijing and Tianjin, the central region includes 75 cities such as Taiyuan and Wuhan, the western region includes 56 cities such as Chengdu and Guiyang, and the northeast region includes 29 cities such as Jilin and Harbin. Three inverse distance square weight matrices are generated after these cities are divided, and the different influences of digital economy on green technology innovation in the three regions of East and West are analyzed by using time-fixed spatial Durbin model.

Table 10: Impact of the Digital Economy on Green Technology Innovation in Different Regions

Variable Name	Eastern Region	Central Region	Western Region	Northeast Region
lnDEI	0.410*** (0.00)	0.039 (0.77)	0.140 (0.26)	0.137 (0.45)
lnURB	-0.312*** (0.00)	0.006 (0.92)	0.283*** (0.00)	0.811*** (0.00)
lnPLB	0.596*** (0.00)	0.417*** (0.00)	0.497*** (0.00)	0.754*** (0.00)
lnYSB	0.874*** (0.00)	0.485*** (0.01)	1.622*** (0.00)	1.088*** (0.00)
lnP	0.526*** (0.00)	1.153*** (0.00)	-1.034*** (0.00)	0.833** (0.01)
lnA	0.959*** (0.00)	1.885*** (0.00)	0.495*** (0.01)	0.711** (0.03)
$lnIS_2$	-0.285 (0.29)	1.541*** (0.00)	-0.733** (0.02)	-1.016*** (0.01)
R^2	0.725	0.5455	0.571	0.559
N	840	750	560	290

According to the regression results in Table 10, there are obvious differences in the impact of variables in different regions on green technology innovation. For the core explanatory variable, digital economy in the eastern region, the ability to promote green technology innovation still exists, the regression coefficient is 0.410, and the promotion effect is greater than the national 0.268. For central, western and northeastern China, the effect of digital economy in promoting green technology innovation is not significant. This paper believes that the possible reasons lie in the following aspects: First, from the data of the eastern region, the overall digital economy index of cities in the eastern region is better than that of other regions, so the improvement effect will be more significant. Secondly, the eastern region embodies most of China's economically developed cities, in order to integrate the economic development framework, government policies will pay relatively high attention to and support the digital economy. This high level of attention and support affects the active green technology innovation in the development of the digital economy.

From the perspective of control variables, the urbanization level shows significant effect in the east, west and northeast, but the effect is different. The east showed inhibitory effects, while the west and northeast showed promoting effects. Compared with the other two regions, the proportion of industrial land and the level of green technology innovation in the eastern region is already very high, and increasing the proportion of industrial land again will cause a counter-effect. The situation is opposite in the west and northeast, so the improvement of urbanization level in the west and northeast will significantly improve the level of green technology innovation.

Each region of population size also passed the significance test, the eastern, central and northeastern regions showed a promoting effect, and the western region showed a inhibiting effect. Western China has a vast geographical area and a relatively low population density. The increase in the scale of population development has not effectively invested in the development of green technology innovation, so it has inhibited the development of local green technology innovation ability.

In the industrial structure, green technology innovation was significantly promoted in the central part of the country and inhibited in the west and northeast. This paper believes that the main reason is that the development of the secondary industry in the west and northeast has not been supported by effective innovative technologies, especially in the northeast, which is the representative of industry, the industrial development mode has not been transformed into green development, so it is inhibited.

The increase in the savings balance of urban and rural residents at the end of the year showed a promoting effect on green technology innovation in the central and eastern regions and the northeast, and the western region had the greatest effect. It shows that more deposits of residents in the western region will flow to green development industries, and the development of green technology innovation will be promoted after receiving funds.

3.3.4 The impact of digital economy on green technology innovation under the heterogeneity of city size

From the above empirical results, it can be seen that population size and green technology innovation ability are positively correlated. In order to explore the reflection of green technology innovation on digital economy under different population sizes, this paper makes adjustments according to the Notice on Adjusting the Classification Standards of City Size issued by The State Council in 2014, and uses the number of permanent urban residents to classify city size. The specific classification standards are shown in Table 11 below.

Table 11: Urban Size Classification (Unit: Per Ten Thousand People)

Before Adjustment		After Adjustment	
Permanent Resident Population <50	Small City	Urban Year-End Total Population≤100	Small and Medium-sized Cities
50≤Permanent Resident Population <100	Medium-sized City	100 < Urban Year-End Total Population≤500	Big City
100≤Permanent Resident Population <500	Large City	500 < Urban Year-End Total Population	Megacities
500≤Permanent Resident Population <1000	Megacities		
1000≤Permanent Resident Population	Metropolis		

After the merger, the number of small and medium-sized cities is 4, the number of big cities is 141, and the number of megacities is 89. The empirical results are shown in Table 12. Both megacities and big cities have passed the 1% significance test, and the impact of digital economy on green technology innovation is positive.

Table 12: Impact of the Digital Economy on Green Technology Innovation in Cities of Different Sizes

	Megacities	Big Cities	Small and Medium-sized Cities
lnDEI	0.284*** (0.00)	0.289*** (0.00)	-1.398 (0.50)
lnURB	-0.152*** (0.00)	0.205*** (0.00)	0.349 (0.93)
lnPLB	0.839*** (0.00)	0.460*** (0.00)	2.217 (0.38)
lnYSB	0.668*** (0.00)	1.180*** (0.00)	-0.132 (0.98)
lnP	-0.139 (0.35)	0.409*** (0.01)	-14.370 (0.57)
lnA	1.665*** (0.00)	1.108*** (0.00)	-1.678 (0.58)
$lnIS_2$	0.525** (0.01)	-0.598*** (0.01)	14.385*** (0.01)
R^2	0.768	0.447	0.054
N	990	1410	40

3.3.5 Robustness test

In order to test the robustness of the regression results, three methods are used in this paper. The first method is to replace the explanatory variable method, replace the core explanatory variable of this paper digital economic development index, and verify the robustness of the regression results. The specific replacement method is to form a new digital economy development index by selecting the three indicators of the number of Internet broadband access users per 100 people, the proportion of computer software and software industry employees and the number of mobile phone users per 100 people in the digital economy as mentioned above, and further verifying the robustness of the regression results. After replacing the core explanatory variables, the impact of the digital economy development index on green technology innovation is significantly positive, which is consistent with the benchmark regression result, and verifies the stability of the regression result.

The second method is to add control variables. The model set up in this paper inevitably has control variables that are not added. Most of the funds for domestic green technology innovation come from local capital financing, and foreign direct investment will affect the local financing environment. Therefore, this paper adds foreign direct investment control variables as a second test method. The results are shown in Table 13 below. The coefficient symbols and significance of core explanatory variables and control variables have not changed. The results show that the conclusion of this paper is still valid after adding control variables.

The third method is to add the lag variable. The development of digital economy starts from the training of technical personnel to the design of corresponding development plans for implementation, and the surrounding cities will have learning and imitation effects after implementation. The realization of the whole process has a certain lag for green technology innovation. Therefore, in this paper, the control variables involved are processed with a one-stage lag and regression is carried out. As shown in Table 13 below, the core explanatory variables still play a promoting role in green technology innovation, indicating that the development of digital economy in the previous year will still affect the green technology innovation in the current year. Therefore, it is necessary to evaluate the feasibility of the plan from a long-term perspective when formulating the development plan of the digital economy. The reliability of the conclusion is verified again by the third method.

Table 13: Robustness Test

Variable Name	Baseline Regression	Replace the core explanatory variable — New Digital Economy Index	Add control variable — Foreign Direct Investment	Explanatory Variable Lagged One Period
lnDEI	0.268*** (3.61)	0.215*** (3.17)	0.256*** (3.49)	0.274*** (3.43)
lnURB	0.154*** (4.64)	0.155*** (4.68)	0.121*** (3.67)	0.165*** (4.69)
lnPLB	0.663*** (7.89)	0.670*** (8.00)	0.684*** (8.16)	0.663*** (7.43)
lnYSB	0.883*** (8.99)	0.917*** (9.50)	0.848*** (8.70)	0.844*** (8.22)
lnP	0.440*** (4.25)	0.469*** (4.39)	0.378*** (3.64)	0.468*** (4.30)
lnA	1.198*** (12.18)	1.217*** (12.41)	1.129*** (11.20)	1.245*** (11.77)
$lnIS_2$	-0.191 (-1.19)	-0.197 (-1.22)	-0.136 (-0.86)	-0.278 (-1.57)
lnFDI	—	—	0.088*** (3.54)	—
R^2	0.638	0.646	0.649	0.636

3.4 Result analysis of obstacle degree model

According to the above analysis results, it can be seen that the development of digital economy has a positive impact on green technology innovation. In order to analyze which factors have the greatest impact on green technology innovation from the characteristics of digital economy itself, this paper analyzes the indicators of digital economy according to the obstacle degree model and processes the data as follows:

1. Calculate the indicator deviation:

$$D_j = 1 - X'_{ij} \tag{10}$$

2. Dyscalculia degree:

$$h_j = D_j * F_j / \sum_{j=1}^{n} (F_j * D_j) \text{、} H_j = \sum h_{ij} \tag{11}$$

In formula (10), (11), D_j represents the indicator deviation; F_j represents the factor contribution, that is, the weight coefficient of each index to the total index system; h_j represents the factor impediment of indicator j.

As can be seen from Figure 2 of the results of the obstacle degree model, in the construction of digital economy indicators, the influence of early input on digital economy indicators exceeded the influence of output and platform user activity since 2013, and continued to remain high in the following years. Secondly, the impact of platform activity is gradually declining, which may represent that the digital economy is gradually changing the way people use traditional media. Finally, the relevant output of the digital economy was at a relatively low level before 2019, and the impact of the relevant output of the digital economy on the digital economy increased rapidly after 2018, indicating that the development of the digital economy has a certain lag effect.

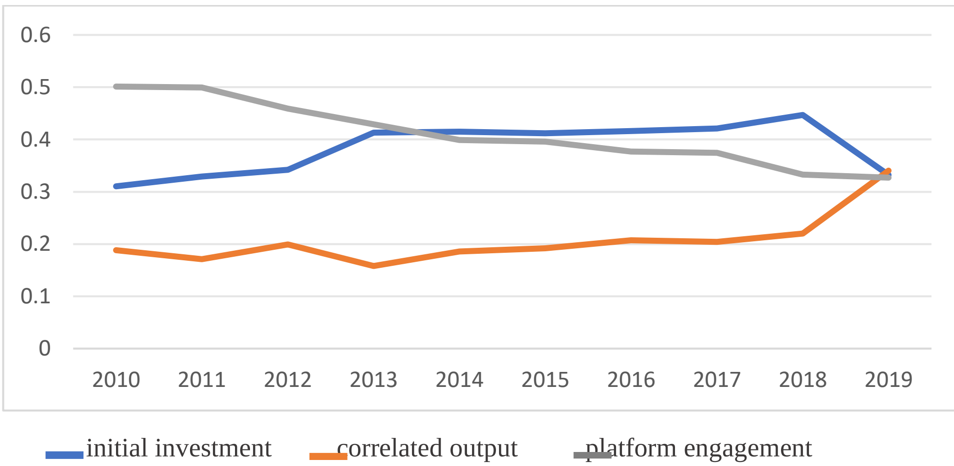

Figure 2: Analysis of Obstacles to Digital Economy Indicators in Various Cities

In view of the impact of digital economy on green technology innovation under the spatial Durbin model, the pre-investment of digital economy has a great impact on the construction of digital economy indicators, which first comes from the criticality of infrastructure construction and technology investment, which lays a solid foundation for supporting research and development and innovation, and promoting the application and commercialization of emerging technologies. Specifically, in the development of digital economy and green technology innovation, attention should be paid to the allocation of funds in the early stage. The utilization of funds, infrastructure construction and personnel training in related industries will build a communication bridge for the development of the two and contribute to the long-term development in the future.

4. Conclusions and policy recommendations

The development of digital economy is an internal link of high-quality development. Studying the relationship between digital economy and environmental development can help the government and enterprises to better balance the relationship between economy and environment. The following conclusions can be drawn from the research findings of this paper:

First, the concentrated distribution trend of green technology innovation in China is obvious, and the geographical characteristics mainly show a "high and low" agglomeration trend. Both the green technology innovation index and the digital economy development index generally show the characteristics of "strong in the east and weak in the west, strong in the south and weak in the north". According to the green technology innovation index and digital economy development index constructed in this paper, most of the green technology innovation index and digital economy development index in various places show an upward trend, but some cities also show a downward trend or a relatively slow development phenomenon, which is speculated to be related to the development positioning of the cities themselves and their own economic foundation. In terms of digital economy indicators, the data characteristics of regional development are also strong in the east and weak in the west. At the same time, it is concluded from the analysis of obstacle degree model that the early investment plays an important role in the development of digital economy, which may be related to the development stage of digital economy construction based on cities in China.

Second, the development of digital economy has a significant promotion effect on green technology innovation and there is a spatial spillover effect, in which the direct effect is significant. According to the spatial Durbin regression results, when other factors remain unchanged, every 1% increase in digital economy development will increase green technology innovation by 0.268%. From the decomposition of the total effect, the direct effect is 0.274, indicating that the development of local digital economy has a positive promoting effect on local green technology innovation.

Third, from the regression results of regional heterogeneity, the promotion effect of digital economy on green technology innovation only exists in the eastern region, and the impact is not significant in the east, west and northeast. From the perspective of the heterogeneity of population size, the promoting effect of the development of digital economy exists in both megacities and big cities, indicating that moderate population growth and aggregation can help promote the growth of green technology innovation ability.

Based on the above conclusions, this paper puts forward the following policy recommendations:

First, continue to invest in the infrastructure of the digital economy and focus on joint development between regions. At present, data resources have become the focus of attention of all people. According to the digital economy development index in this paper, the developm20ent level of different cities is different, and the eastern region is obviously stronger than other regions. Therefore, the government should pay more attention to avoid the aggravation of knowledge gap while increasing investment. In order to increase investment in the digital economy in some cities and avoid the emergence of knowledge gaps, digital economy education and training must be strengthened to improve the digital skills and knowledge of urban residents, including computer science and digital technology education for students, and continuous digital training opportunities for adults. Secondly, since the barrier degree model analyzes the initial investment as the primary barrier degree of the digital economy, promoting the popularization of digital infrastructure and ensuring the wide accessibility of digital tools and the Internet is an effective starting point for building a digital China. In addition, digital innovation and entrepreneurship are encouraged, and local businesses are provided with support and incentives to promote the development of the digital economy and increase job opportunities. Finally, governments, educational institutions and businesses should actively collaborate to develop comprehensive digital strategies to ensure the inclusive development of the digital economy.

Second, the development of green technology innovation has a time lag and the direct effect is more significant. Cities in the eastern region should pay more attention to the long-term research of green technology innovation and take the quality of results transformation as the development goal. The key is to increase R&D investment in policy management of time lag. By directly financing research projects, providing innovation incentives, and establishing green technology innovation funds, technology development and market maturity can be accelerated. Second, it is necessary to create a network of research and development collaborations, enabling governments, companies, and research institutions to share resources and knowledge, thereby reducing duplication of effort, reducing costs, and driving technological evolution. It is also key to create incentives, including tax breaks, subsidies and emissions trading, to make green technologies more attractive in the market and encourage companies to adopt them to further promote sustainable development and environmental goals. In the process of investment and development, other regions should pay more attention to the positive effects brought by population agglomeration, formulate appropriate population size growth plans, observe the change between population size and actual output, and avoid the negative effects brought by time lag.

Third, pay close attention to diversity among cities so that policies can be tailored to specific geographical conditions. While pursuing the goal of "dual carbon", both digital economy and green technology innovation have theoretically demonstrated the inhibition effect on carbon emissions. According to the results of this paper, the development of digital economy will also promote the development of green technology innovation, and cities should cooperate with each other according to their own development positioning and characteristics. For example, cities that have no significant promotion effect in the heterogeneity of regions and cities can consider joint development with other cities. To maximize the carbon reduction potential of green technology innovation and the digital economy.

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