An Empirical Study on the Impact of Digital Economy Development Level on the Efficiency of Green and Low Carbon Transition in Chinese Cities

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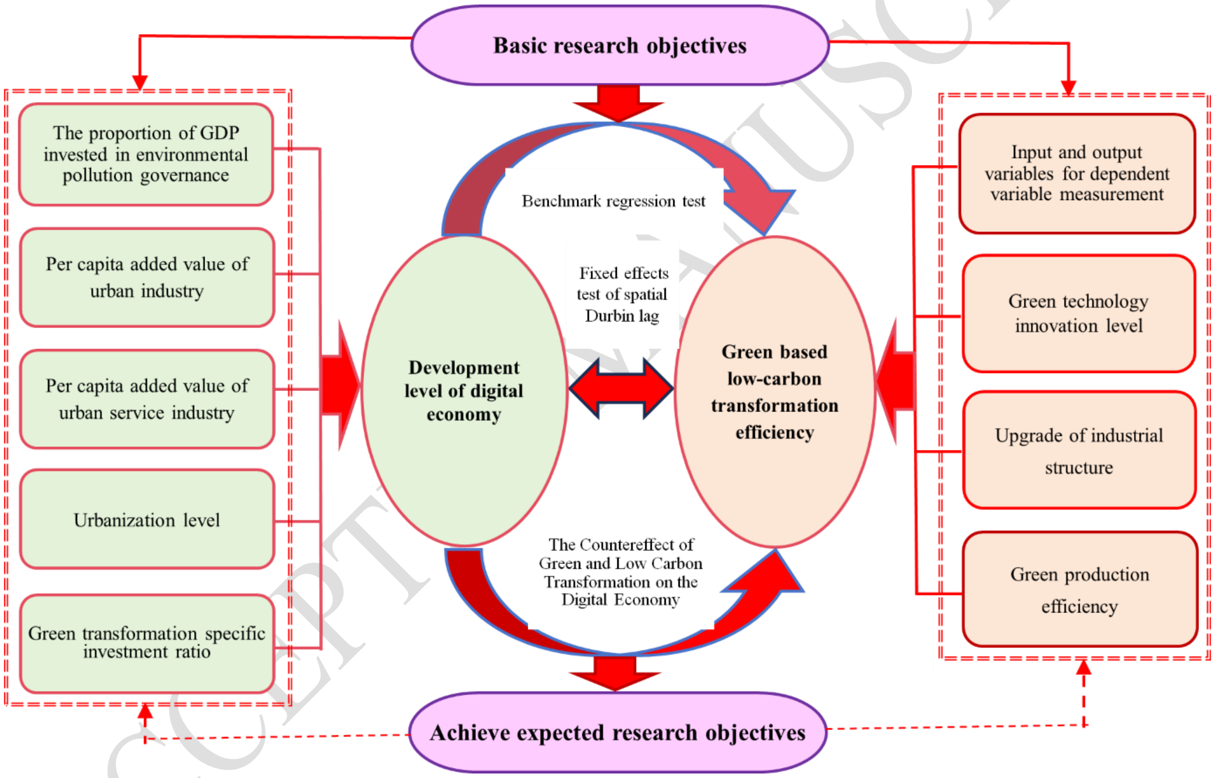
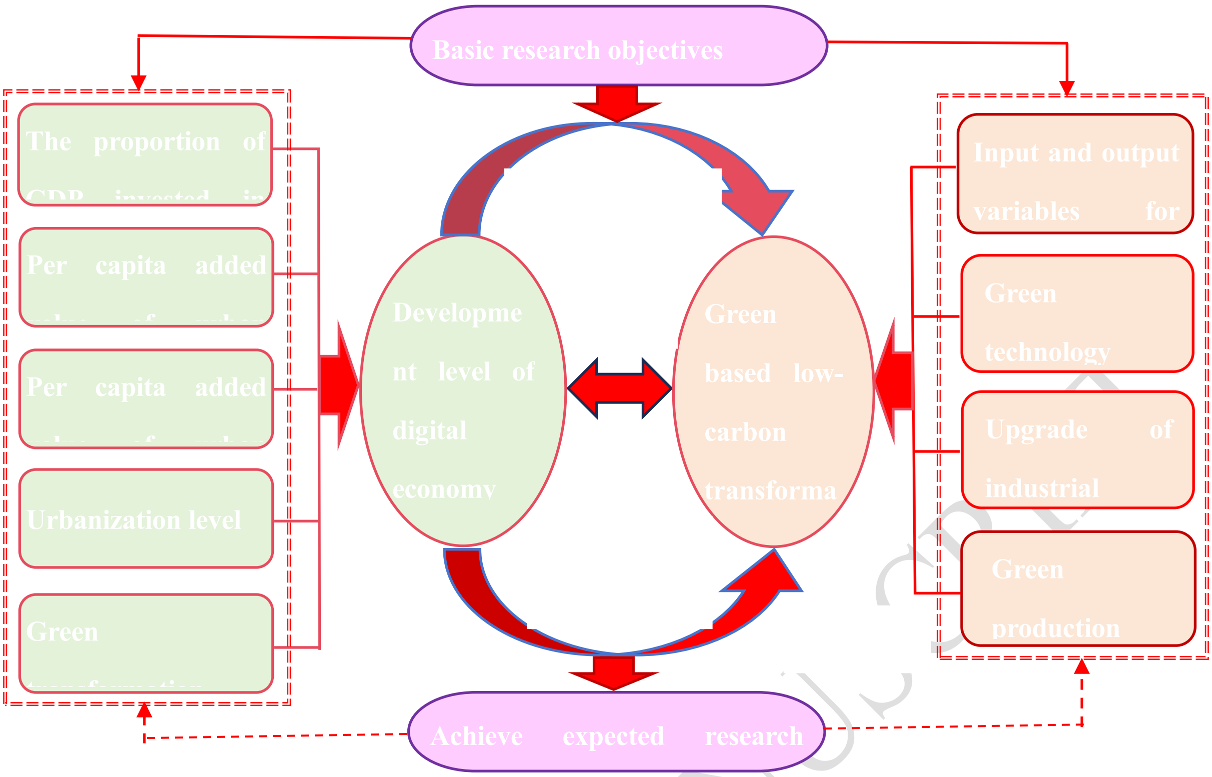
Graphical Abstract





ABSTRACT

As China's economic and social development enters a new growth stage, urban green transformation has gradually become an important means to promote high-quality development. In order to explore the effective methods of the impact of China's digital economy development level on the efficiency of urban green low-carbon transition, this paper, based on the statistical data of 263 prefectural-level cities in China during the period of 2012-2021, adopts the "China Digital Economy Development Index Report (2023)" jointly developed by the Ministry of Industry and Information Technology of China and the Zero One Think Tank, as well as the five selected control variables , measures the efficiency of urban green low-carbon transition by using the SBM model and examines the impact of driving factors on urban green low-carbon transition by using the spatial Durbin lagged panel fixed-effects model. the influence of driving factors on the efficiency of green low-carbon transition in Chinese cities. It was found that: the digital economy index showed a positive correlation with urban green transition efficiency, and the corresponding positive influence coefficient was 0.523, and the influence of control variables on urban green transition efficiency showed differentiation characteristics, among which: the investment rate in environmental pollution control, the contribution rate of GDP in the service industry, and the professional investment rate in green transition showed a positive correlation with urban green transition efficiency, and the corresponding influence coefficients were 0.437, 0.304 and 0.348; the contribution rate of urban industrial GDP and urbanization level show inverse correlation with the efficiency of urban

green transformation, and the corresponding inverse impact coefficients are -0.412 and -0.276, respectively. The conclusions of this paper are of great practical value for the formulation of policies to improve the efficiency of urban green transformation.

Keywords: digital economy; green transition; transition efficiency; green low-carbon; Chinese cities

1. Introduction

With the rapid development of the global economy, the intensity of energy consumption and carbon emissions has shown a downward trend, and the efficiency of urban green low-carbon transformation has shown a rising trend (Sun and Liu, 2023). In the face of climate change and environmental pollution caused by the continuous rise in the scale of global energy consumption and carbon emissions, green low-carbon transformation has become a common development concept and goal for all countries in the world (Shi and Shi, 2023).In 2015, the United Nations adopted the 2030 Agenda for Sustainable Development, which put forward 17 sustainable development goals (SDGs), including protecting the environment, addressing climate change, and promoting clean energy, which are closely related to the green and low-carbon transition (Martinez and Mueller, 2015). In the same year, the Paris Climate Agreement was reached, providing a legal framework and guidelines for global action to address climate change (Falkner, 2016). In 2020, Chinese President Xi Jinping announced at the 75th United Nations General Assembly that China would strive to achieve "carbon peaking" by 2030 and "carbon neutrality" by 2060. This is known as the "dual carbon" goal in China, and represents a solemn commitment to the global response to climate change (Zhang, 2021). According to China's Energy Consumption Statistics Report, China's total energy consumption in 2023 will be 5.720 billion tons of standard coal, an increase of 5.7% over the previous year, and the total energy consumption CO_2 emissions estimated according to CO_2 molecular structure will be 20.973 billion tons, and China's per capita carbon emissions will be about 14.77 tons, an increase of 147.17% over the 2013 figure of 6 tons per capita and an average increase of 13.29% per year This far exceeds the growth rate of China's per capita GDP (Jiang et al., 2024). Therefore, the task of realizing the "dual-carbon" goal in China is very arduous, in which case making full use of the digital economy to promote the continuous improvement of the efficiency of the green and low-carbon transformation of Chinese cities has become an important issue that needs to be solved urgently.

According to statistics from the China Institute of Information and Communication Research, the total size of China's digital economy is expected to be 56.1 trillion yuan in 2023, accounting for 44.50% of GDP. The digital economy first arose in the United States and was pioneered by Tapscott, a famous American economist, and the development of the digital economy pointed out the direction of incompetent or low-

energy-consuming production for the world economy (Tapscott, 1994). After the emergence of the digital economy, it was not favored by some relatively backward countries in the early stage, which thought that the digital economy was just a castle in the air or a flower in the water (Sun and Wang, 2004). Developed countries are optimistic about the development trend of digital economy. After the United States put forward the concept of digital economy, the U.S. Department of Commerce released the "Emerging Digital Economy Report" in June 1999 and increased the scope of the digital economy statistics from the national perspective (Soete, 2000); Japan began to standardize the concept of digital economy in 1997, and put forward the "Industrial Re-emergence" strategy (Industrial Re-emergence, 2008); and Japan has been the first country to develop digital economy. Industrial Re-emergence" strategy in 2008 (Chiavacci, 2018); Germany's digital economy development slightly lags behind the U.S. and Japan, the German government proposed the "German Platform Industry 4.0" in 2013, released the "German Platform Industry 4.0 Development Report" in 2015 and formulated a digital economy development plan for the next 20 years (Wilkesmann and Wilkesmann, 2018). China's digital economy development lagged slightly behind developed countries and started to prioritize digital economy development after the 21st century. It was only in 2018 that the Chinese government released the Strategic Outline for the Development of the Digital Economy and began to study the development strategies and tactics of China's digital economy from different aspects (Yao and Zhang, 2021), and by 2020 the size of China's digital economy had reached 39.20 trillion yuan, making it one of the fastest-growing countries in the world in terms of digital economy.

Along with the development of China's digital economy, the Chinese government has begun to pay attention to urban green low-carbon transition and high-quality urban development, and leveraging various means to enhance the efficiency of China's urban green low-carbon transition has gradually become a strategic task for the Chinese government (Song et al., 2020, Ren and Sun, 2022). Chinese scholars' research on urban green and low-carbon transition began in 2002, and the earliest research on green and low-carbon transition was on the green and low-carbon transition of natural ecology (Xu et al., 2022), and then its research field gradually shifted to the green and low-carbon transition of urban industry, focusing on the green transition of the use of energy in urban industrial production (Wei, 2022); Another direction of green transition is the green low-carbon transition of energy consumption in residents' life, including the green transition of energy consumption in residents' life and private cars. Many city governments in China have promised that the proportion of new energy vehicles will exceed than 50% in 2025, which makes the green low-carbon transition of energy consumption in China's urban industry gradually becoming a reality (Su, 2021).

In addition to the above two aspects of research content, academic research on digital economy and green low-carbon transition has gradually focused on the research direction of digital economy on the efficiency of green low-carbon transition in Chinese cities (He et al., 2022, Wang, 2023). In fact, the driving factors affecting the efficiency of green low-carbon transition in Chinese cities are not only the digital economy, but also some control variables related to the development of the digital economy (Zhang and Zhong., 2023). In the process of research on this issue, the control variables have a wide range of choices, which results in research results with their own characteristics (Wang, 2023). In addition to the differences in the choice of control variables, the differences in the research on the impact of digital finance on the efficiency of green transition are also manifested in the differences in research perspectives, the differences in research methodologies and the differences in research contents, etc.

There are many different research results just from the choice of research methods, such as the test results using only the basic regression model (Wang et al., 2022), the test results using the Durbin's variance model, the test results using the spatial Durbin's lagged fixed-effects model (Feng et al., 2023), the test results considering the different mediating effects, and the test results considering the gate threshold of the different model test results and so on (Jia et al., 2022).

As can be seen from the literature review above, the research on this topic focuses on three main aspects: the digital economy, green and low-carbon transition, and the impact of the digital economy on the efficiency of green and low-carbon transition of urban energy consumption. This research topic has global research characteristics and importance, but due to the differences in the economic development and social system of each country, the research on the same topic has different research contents and unique attributes, and the common problems in the research on this issue are: the measurement of the efficiency of the green transition, the selection of the driver test model, and the construction of the indicator system and data sources (Hou et al. 2023). The potential contribution of this paper lies in solving the existing major problems, the key lies in solving the effective measurement of the efficiency of green and low-carbon transformation of urban energy consumption, constructing the indicator system of digital economy as the main content of the driver, reflecting the characteristics of this paper, as well as rationally carrying out the design of empirical tests, and choosing effective empirical test methods to improve the test effect.

2. Materials and methods

2.1 Theoretical model and research hypothesis

According to the research design of this paper, the purpose of this paper is to: utilize the SBM model to scientifically measure the efficiency of green low-carbon transition of energy consumption in Chinese cities based on the simultaneous consideration of three mediating variables of green low-carbon transition efficiency. The empirical test of the dependent variable drivers utilizes a combination of basic regression, mediator variable test and spatial test, and selects the digital economy explanatory variables as well as five control variables, including the investment rate in environmental pollution control, the contribution rate of urban industrial GDP, the contribution rate of service industry GDP, the level of urbanization, and the rate of investment dedicated to urban green transition, and utilizes a combination of the basic regression model and the spatial Durbin's lagged panel fixed-effects model to test the impact of the main drivers on the green and low-carbon transition efficiency of Chinese cities. The combination of basic regression model and spatial Durbin lagged panel fixed effect model was used to test the extent of the influence of the main drivers on the efficiency of green low-carbon transition of energy consumption in Chinese cities (Liu et al., 2022). In order to realize the empirical test of the drivers of green low-carbon transition efficiency in Chinese cities, it is necessary to make the corresponding premise assumptions for the basic theoretical test by analyzing the mechanism of the role of the independent variables on the dependent variables (Liao, 2023). According to the research objectives of this paper as well as the research design, the theory and methods of quantitative economics are utilized to construct the role mechanism model for the empirical test of this paper with full consideration of the core content of this paper, and simultaneously reflects the research ideas of this paper at the same time, and its model structure and main content are shown in Figure 1.

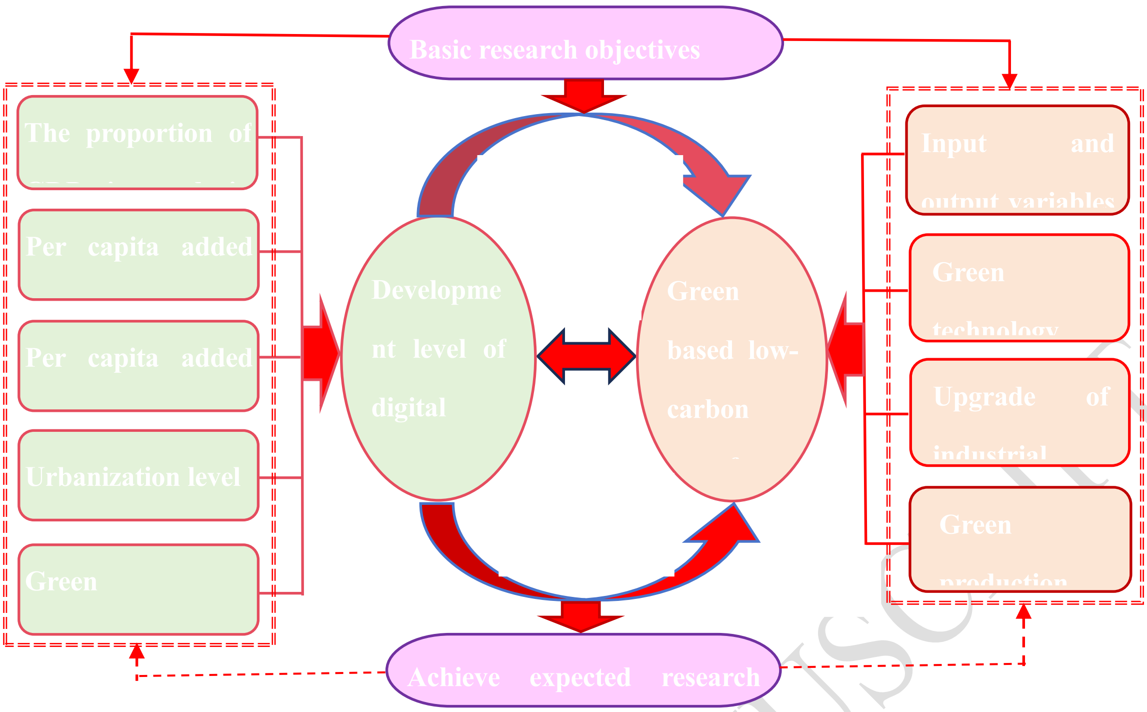


Figure 1. Mechanisms of the digital economy's role in the efficiency of the urban green transition

The digital economy is a new type of economic form in which data resources are the key industrial elements, modern information technology and the Internet are the main carriers, and a new form of industry in which equity and efficiency are fused through the promotion of the fusion of information and communication technologies and their applications, with the promotion of the digital transformation of all elements as the important driving force. The digital economy is manifested at the technical level by emerging technologies such as big data, cloud computing, Internet of Things, blockchain, artificial intelligence, 5G communications, etc.; at the application level by new business forms such as "new retail" and "new manufacturing"; and at the institutional environment level by regulations, norms, planning and programs of the digital economy. economy regulations and norms, planning programs and other important elements. The selection of control variables in this paper is mainly based on two aspects: first, the important factors affecting the efficiency of China's green and low-carbon transformation in the selected Chinese cities, and the increase in the selection of indicators to drive the improvement of China's urban green transformation efficiency; second, fully considering the theory of improving the efficiency of China's urban green transformation, that is, by maximizing output while minimizing input, the explanatory variables and control variables selected in this paper are based on the above two aspects. Since the digital economy is an important form and key means of promoting China's green and low-carbon transformation, the digital economy development index is selected as the explanatory variable to promote the efficiency of China's green and low-carbon transformation, and five control variables are selected at the same time, including the proportion of investment in environmental pollution control in GDP, per capita urban industrial added value, per capita added value of urban services, urbanization level, and the proportion of special investment in green transformation. Since the control variables mainly affect the efficiency of urban green and low-carbon transformation through intermediary variables, according to the actual situation of China's urban green and low-carbon transformation, three intermediary variables were mainly selected: the level of green technological innovation, industrial structure upgrading, and green production efficiency.The digital economy has completely changed the original production mode of using energy consumption to replace GDP, and promoted the development and upgrading of the green low-carbon transformation of Chinese cities. Based on the analysis of the mechanism in this regard, we put forward the first premise hypothesis of this paper, H_1: the development of the digital economy can promote the enhancement of the efficiency of the green low-carbon transformation of cities. According to the key content in Figure 1, the impact of the digital economy on the green low-carbon transition of Chinese cities is usually manifested in the promotion of the efficiency of urban green low-carbon transition through the mediating variables of the level of green technological innovation, the upgrading of industrial structure, and green production efficiency (Zhang et al., 2022, Fang et al., 2024). Firstly, the digital economy has changed the direction of traditional technological innovation, leading urban technological innovation to the non-polluting green development field, which makes the improvement of urban green and low-carbon transition efficiency have a greater impetus, based on the analysis of this mechanism to put forward the second premise of this paper's hypothesis H_2 : the digital economy through the promotion of green technological innovation to promote the improvement of urban green and low-carbon transition efficiency. Secondly, the GDP ratio of emerging industries in China reflects the status of industrial structure upgrading, and the content of industrial structure upgrading is to encourage the development of non-polluting industries, based on this consideration, the third premise hypothesis of this paper is proposed H_3: the digital economy promotes the improvement of the efficiency of the urban green low-carbon transformation by upgrading the industrial structure. Finally, the development of digital economy promotes the growth of urban green GDP, and the ratio of green GDP to the resident population of the city is called green production efficiency. Therefore, the development of digital economy usually promotes the efficiency of urban green low-carbon transition by improving green production efficiency (Shen et al., 2023). Based on this aspect, the fourth premise hypothesis of this paper is proposed H_4 : The digital economy promotes the efficiency of urban green low-carbon transition by promoting the increase of urban green GDP.

2.2 Study population and data sources

In order to empirically test the spatial impact of the digital economy index on the efficiency of green and low-carbon transformation of urban energy consumption, this paper selects 263 prefectural-level cities, sub-provincial-level cities, and municipalities directly under the central government in China as the research objects (cities with incomplete, incomparable, or withdrawn data were excluded), and based on the statistical information of the Statistical Yearbook, the Energy Statistical Yearbook, the Urban Statistical Yearbook, and the Bulletin on the State of the Ecological Environment at the national and provincial levels. Reference was made to the relevant statistics of some prefecture-level cities, taking into account that the Chinese government's public disclosure of environmental pollution statistics began in 2012 (Liu et al., 2021). Therefore, the data period chosen for the study of this paper is: 10 years of basic data during 2012-2021. According to the research design, the data size of the empirical test was a total of 2630, and the selection of correlated or similar indicators was avoided as much as possible in order to minimize the issue of collinearity among the selected driving factors indicators (Li and Ding, 2022). In addition, because the certain indicators chosen for the research design need to be obtained through calculation, and there are individual indicators in the calculation process that need to be obtained through correction or prediction, in this case, the authors have made a certain degree of correction to the calculation of the individual basic information, and their numerical corrections will not affect the final results of the study.

3. Measurement of the efficiency of the urban green and low-carbon transition

3.1 Modeling the efficiency of urban green and low-carbon transition

Urban green low-carbon transition is a strategic proposition to overcome the threat to the climate and the environment posed by the large amount of energy consumption in the process of urban economic development along with the development of China's urban economy, and its core connotation refers to the promotion of the fossilized energy consumption in the process of urban economic development to gradually transform the use of clean energy production, to completely eliminate the current situation of climate change in terms of energy consumption as well as air pollution, and to promote the green and low-carbon development of China's urban economy. The core meaning of the topic is to promote the gradual transformation of fossil energy consumption in the process of urban economic development to clean energy production, completely eliminating energy consumption, climate change and air pollution, and promoting the green low-carbon development of China's urban economy. According to the research results of China's Beijing Zhi Yan Ke Xin Consulting Co., Ltd, in 2022, China's clean energy production

is initially estimated to reach 1.198 billion tons of standard coal, accounting for 26.9% of the total domestic primary energy production, in order to cope with climate change generated by energy consumption, China's urban development strategy is gradually moving towards the service industry, which consumes very little energy during the process of generating GDP, and basically falls into the category of Low-energy consumption or non-polluting industries. By 2023, the added value of China's service sector will account for 54.6% of GDP, and the contribution of final consumption expenditure to economic growth will reach 82.5%. This indicates that the green low-carbon transition efficiency of production in Chinese cities has exceeded 70%, implying that it is likely to be even higher. In order to measure the green low-carbon transition efficiency of Chinese cities, this paper introduces an improved data envelopment SBM model, which takes into account energy consumption and non-expected output. The SBM model, or Slacks-Based Measurement model, was initially proposed by the Japanese scholar Tone in 2001 (Tone et al. ,2001). The original SBM model does not consider energy consumption and non-desired outputs, while this study improves this model by mainly adding the consideration of non-desired outputs, such as energy inputs and environmental pollution, in order to effectively measure the efficiency of the green and low-carbon transition of 263 cities in China. Based on the basic model of SBM, the modified model for measuring the efficiency of green low-carbon transition (*LLTE*) of cities is shown as follows:

$$LLTE = \min \frac{1-\frac{1}{k}\cdot\sum_{r=1}^{k}\left(S_{rt}^{-}/x_{rt}\lambda_r\right)}{1+\left[\frac{1}{m}\cdot\sum_{i=1}^{m}\left(S_{it}^{+}/y_{it}\lambda_i\right)+\frac{1}{n}\cdot\sum_{j=1}^{n}\left(S_{jt}^{u-}/y_{jt}^{u}\lambda_j\right)\right]} \qquad (1)$$

$$S\cdot t.\begin{cases}\sum_{r=1}^{k} x_{rt}\lambda_r + S_t^{-} = X_t\\ \sum_{i=1}^{m} y_{it}\lambda_i - S_t^{+} = Y_t\\ \sum_{j=1}^{n} y_{jt}^{u}\lambda_j + S_t^{u-} = Y_t^{u}\\ \sum_{r=1}^{s}\lambda_r = 1, \sum_{i=1}^{m}\lambda_i = 1, \sum_{j=1}^{n}\lambda_j = 1\\ S_t^{-}, S_t^{+}, S_t^{u-}, \lambda_r, \lambda_i, \lambda_j \ge 0\end{cases}$$

In the above equation: S_{rt}^{-} is the matrix of slack variables of input indicators, X_{rt} is the matrix of input variables, S_{jt}^{+} is the matrix of slack variables of desired output indicators, S_{jt}^{u-} is the matrix of slack variables of non-desired output indicators, y_{it} is the matrix of desired output variables, y_{jt}^{u} is the matrix of non-desired output variables, and λ is the relative weights. Determine the main indicators to measure

the efficiency of green low-carbon transition in Chinese cities and according to the statistical information provided by the government and the results of the indicators calculated in this paper, the statistical results of the main indicators are given in Table 1.

Table 1. Descriptive statistics of the indicators measuring the efficiency of the urban green transition

Variable type	variant	unit (of measure)	weight	maximum values	minimum value	average value
throw oneself into	Gross fixed capital of urban industry	billions	0.2	11850	560	1560
	Total urban industrial liquidity	billions	0.15	5600	1200	3250
	Participants in the green transition	all the people	0.15	2100	820	1280
	Total investment in urban green transformation	billions	0.3	4600	1050	2100
	Scale of urban energy inputs	Tons of standard coal	0.2	21000	2600	8910
Expected outputs	Value added of urban green industry	billions	1	11000	1600	8950
Non-expected outputs	Urban energy consumption per capita CO_2 emissions	ton (loanword)	0.4	9500	4100	6800
	Scale of municipal industrial wastewater discharges	tons	0.2	18500	805	6520
	Scale of urban industrial emissions	billion M^3	0.2	8210	820	6820
	Scale of municipal industrial solid waste emissions	tons	0.2	870	202	385

Since the National Bureau of Statistics does not have statistical data on the efficiency of urban green and low-carbon transformation, it is necessary to calculate the green transformation efficiency of 263 cities in China based on the concept of urban green and low-carbon transformation, using the modified SBM model above and the selected input and output indicators of urban value creation and the relevant basic

data, and the interval of the results of the calculations ranges from 0.2671 to 0.7836, that is, the maximum value of green and low-carbon transformation efficiency of the 263 prefectural-level cities in China is 0.7836, and the minimum value is 0.5127. The maximum value of green low-carbon transition efficiency of 263 prefecture-level cities is 0.7836, the minimum value is 0.2671, and the mean value is 0.5127.

3.2 Empirical test model construction of drivers

According to the framework diagram of the research idea, it can be seen that the driving factors of the efficiency of urban green low-carbon transformation chosen by the research design of this paper are: the level of development of the digital economy, the rate of investment in environmental pollution control, the rate of contribution of industrial GDP, the rate of contribution of service industry GDP, the level of urbanization, and the rate of investment dedicated to urban green transformation. In order to test the degree of influence of the above six driving factors on the efficiency of urban green low-carbon transformation, the basic regression model is first given, and the basic formula of the test model is as follows:

$$LLTE_{it} = \alpha_0 + \alpha_1 DE_{it} + \sum_{i=2}^{n} \alpha_i X_{it} + \mu_i + v_i + \varepsilon_{it} \quad \textbf{(2)}$$

In the above equation: $LLTE_{it}$ is the city's green low-carbon transition efficiency, DE_{it} is the city's digital economy development level, X_{it} is the control variable, μ_i is the city dummy variable, v_i is the time dummy variable, ε_{it} is the stochastic perturbation term, α_0 is the constant term of the test equation, and α_i is the coefficient of the independent variable of the test equation. In order to test the influence of mediating variables on the efficiency of urban green low-carbon transformation, three mediating variables of digital economy on the efficiency of urban green low-carbon transformation are introduced to test the indirect influence of its intermediate variables on the efficiency of urban green low-carbon transformation. The three intermediary variables introduced in this paper are: green technology innovation level, industrial structure upgrading and green production efficiency. The green technology innovation level uses the green technology innovation index published by Zero2IPO; the industrial structure upgrade uses the GDP ratio of the output value of emerging industries in each city; and the green production efficiency uses the ratio of the green GDP to the end resident population in each city. Using the mediator variable to replace the dependent variable, the following mediator variable test model can be obtained as follows:

$$\begin{cases} MV_{it} = \beta_0 + \beta_1 \ln DE_{it} + \sum_{i=2}^{n} \beta_i X_{it} + \mu_i + v_i + \varepsilon_{it} \\ LLTE_{it} = \gamma_0 + \gamma_1 \ln DE_{it} + \gamma_2 MV_{it} + \sum_{i=3}^{n} \beta_i X_{it} + \mu_i + v_i + \varepsilon_{it} \end{cases} \quad (3)$$

In the above equation, MV_{it} is the mediating variable, and other letters have the same meaning as before. In order to test the spatial spillover effect of the impact of the level of digital economy development on the efficiency of urban green and low-carbon transition, it is necessary to introduce the spatial Durbin lagged panel fixed-effects model, and there are mainly three basic forms of the introduced spatial relative weights: (1) spatial adjacency matrix (W_1). That is, the relative weights matrix composed of 0 and 1, two cities adjacent to take the value of 1, two cities are not adjacent to take the value of 0; (2) economic spatial matrix (W_2). If the GDPs of two neighboring cities are represented by GDP_i and GDP_j respectively, then: W =$_2$ $\left(GDP_i - GDP_j\right)^{-1}$; (3) Spatial geospatial matrix (W_3). This spatial matrix is the weighted average of the spatial adjacency matrix and the spatial economic matrix, i.e., W = $W_3 \xi_1$ + (1- ξ) W_2. Thus, the spatial Durbin lagged panel fixed effects model can be expressed as follows:

$$LLTE_{it} = \lambda_0 + \lambda_1 df_{it} + \sum_{i=2}^{n} \lambda_i X_{it} + \rho_1 \sum_{i=1}^{m} W_{it} df_{it} + \rho_2 \sum_{i=1}^{n} W_{it} X_{it} + \mu_i + v_i + \varepsilon_{it} \quad (4)$$

4. Results

4.1 Descriptive statistics of empirical test variables

In order to test the impact of the digital economy on the green low-carbon transition efficiency of 263 cities in China, based on the basic data provided by the China Statistical Yearbook, and taking into account the lack of statistics from Hong Kong, Macao, Taiwan and Tibet Autonomous Region in the available statistics, as well as the lack of basic data in some cities to calculate the efficiency of the green low-carbon transition, 263 prefectural-level cities out of the 293 cities in China were selected to conduct the green low-carbon transition efficiency measurement. On this basis, in order to empirically test the driving factors affecting the efficiency of green low-carbon transition in Chinese cities, based on the basic data collected by the authors and some special indicators calculated by using the basic data, this paper gives the descriptive statistical results of all dependent variables, mediating variables and independent variables as shown in Table 2.

Table 2: Descriptive statistics for empirical test variables

change the name	variable conforms to	sample size	average value	minimum value	maximum values

Efficiency of the urban green transition	**LLTE**	**2630**	**0.5254**	**0.2671**	**0.7836**
Digital Economy Development Index	**DF**	**2630**	**1.51**	**0.18**	**2.84**
Level of green technology innovation	**TIL**	**2630**	**0.5077**	**0.1528**	**0.8625**
Upgrading of industrial structure	**UIS**	**2630**	**0.4566**	**0.1106**	**0.6126**
Green productivity	**GPE**	**2630**	**0.1241**	**0.0826**	**0.3182**
Investment rate in environmental pollution control	**PIR**	**2630**	**0.0145**	**0.0098**	**0.0209**
GDP contribution of urban industry	**PIG**	**2630**	**0.37**	**0.18**	**0.56**
GDP contribution of urban services	**PSG**	**2630**	**0.58**	**0.21**	**0.81**
urbanization level (of a city)	**UL**	**2630**	**0.6579**	**0.3631**	**0.9526**
Rate of investment dedicated to the green transition	**PIP**	**2630**	**0.0234**	**0.0035**	**0.0453**

In the above table: the efficiency of the city's green transition is scientifically measured using the SBM model, and only statistics are given due to the huge scale of the measurement; The Digital Economy Index uses the "China Digital Economy Development Index Report (2023)" jointly developed by the Ministry of Industry and Information Technology of China and the Zero One Think Tank; the investment rate in environmental pollution control uses the ratio of the total amount of investment in all aspects of the city's use of environmental pollution control to the city's GDP. Studies by Chinese scholars (Han et al., 2018; Liu et al., 2021) have shown that the higher the contribution of industrial added value to GDP, the greater the relative energy consumption intensity, which makes the efficiency of China's urban green transformation negatively correlated; the specialized green transition funds refer to the ratio of the city's total investment dedicated to green transition to its permanent resident population at the end of the

period, other indicators are from government statistics, and the three mediating variables have been described earlier.

4.2 Test results of the basic regression model

In order to reduce or avoid the existence of multicollinearity between the selected driver variables, it is necessary to calculate Variance Inflation Factor, denoted as VIF value, for the selected driver variables, a variety of software can calculate the VIF, in this paper, we use the MATLAB software to calculate the VIF = 2.016<5 (10), which verifies that the driver variables do not existence of multicollinearity. According to the test results, since Hausman<1‰, then the fixed effect model should be selected, using the benchmark regression fixed effect model to test the basic hypothesis H_1, the specific test results are detailed in Table 3.

Table 3: Benchmarking regression results for drivers of green low-carbon transition efficiency

Variables	(1) OLS	(2) Dual non-fixed	(3) Random effects	(4) Double fixed effects
DE	0.216^{***} (3.48)	0.305^{***} (4.06)	0.516^{***} (4.25)	0.523^{***} (4.26)
PIR		0.379^{***} (4.46)	0.427^{***} (4.37)	0.437^{**} (2.38)
PIG		-0.401^{***} (-4.37)	-0.406^{***} (-4.07)	-0.412^{***} (-3.85)
PSG		0.259^{***} (4.64)	0.296^{**} (2.162)	0.304^{**} (2.38)
UL		-0.112^{**} (-2.26)	-0.226^{*} (-1.89)	-0.276^{**} (-2.27)
PIP		0.296^{***} (4.16)	0.337^{**} (2.42)	0.348^{**} (2.52)
Constant	-	0.819^{***} (4.16)	0.875^{***} (4.16)	0.895^{***} (3.637)
N	2630	2630	2630	2630
R^2	0.146	0.152	0.212	0.295
City-F	Yes	Yes	Yes	Yes
Year-F	Yes	Yes	Yes	Yes

Note: *** is passing the 1% confidence test, ** is passing the 5% confidence test, * is passing the 10% confidence test, and the t-test result values are in parentheses.

According to the test results in Table 1, it is obvious that all six independent variables passed the significance test with a confidence level of 10%, and most of the variables passed the significance test with a confidence level of 1%. According to the results of the base test of the double fixed effects test model, the coefficient of the impact of digital finance on the efficiency of urban green transformation is 0.483. Although the value added of the service industry per capita has an upgrading effect on the efficiency of urban green transformation, its upgrading is less than the inhibiting effect of the value added of the industry on the efficiency of urban green transformation, therefore, it is more important to control the value added of the city's industry than to enhance the value added of the service industry, without the support of industrial development, the development of the service industry will be more important than the development of the service industry. Without the support of industrial development, the development of the service industry has no foundation, which also shows that the green transformation of urban energy consumption is the way to solve the long-term development of China's economy, and the adjustment of the industrial structure alone can't solve the fundamental problem of improving the efficiency of green transformation.

4.3 Mediated effects test results

Although the complete elimination of fossil energy is the key to improving the efficiency of China's urban green transformation, the current share of clean energy in all energy sources in China is only about 20%, so it is unrealistic to fully use clean energy for economic development in the short term. In the current situation where China is still fully dependent on fossil energy, we must promote the efficiency of urban green transformation through green technological innovation, industrial restructuring, and improvement of green production efficiency.

Table 4: Test results for intermediary variables

Variables	Green Technology Innovation		Upgrading of industrial structure		Green productivity	
	TIL	LLTE	UIS	LLTE	GPE	LLTE
TIL		0.456*** (4.82)				
UIS				0.673*** (5.18)		
GPE						0.546*** (4.64)
DE	0.726*** (4.89)	0.365 (5.18)	0.628 (5.32)	0.381 (5.47)	0.526 (4.84)	0.392 (4.51)
Constant	-0.682*** (-7.27)	0.465*** (6.28)	0.462*** (5.37)	0.386*** (5.27)	0.501*** (5.16)	0.418*** (4.89)

N	**2630**	**2630**	**2630**	**2630**	**2630**	**2630**
R^2	**0.384**	**0.273**	**0.427**	**0.289**	**0.503**	**0.302**
Controls	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
City-F	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Year-F	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**

Note: * is passing the 1% confidence test, ** is passing the 5% confidence test, * is passing the 10% confidence test, and the t-test result values are in parentheses.**

4.4 Spatial spillover test results

In order to test the spatial spillover effect of the efficiency of urban green low-carbon transition, this paper introduces a spatial Durbin panel model. In order to select an effective spatial Durbin model, LM test, LR test, Wald test and Hausman test were conducted respectively. The test results of LM-Lag and Robust LM-Lag were 8.237 and 4.218, which passed the significance test with a confidence level of 1% and 5%, respectively, and thus the spatial error model was rejected; and the test of spatial lag model was 7.832 and 2.371, which passed the significance test with a confidence level of 1% and 10%, respectively. The results were 7.832 and 2.371, which passed the test of significance with a confidence level of 1% and 10%, respectively, and also rejected the spatial lag model; since the results of the LR test and the Wald test passed the test of significance with a confidence level of 1%, the original hypothesis was rejected, i.e., the spatial Durbin model does not degenerate into the spatial error model as well as the spatial lag model; the results of the Hausman test were 78.51, which The Hausman test result is 78.51, which passes the test of significance with a confidence level of 1%, which indicates that the test results of choosing the random effects model and the fixed effects model will be better. Accordingly, the specific test results are shown in Table 5.

Table 5: Results of tests for spatial spillover effects

Variables	Space Dobbins	direct effect	indirect effect	aggregate effect
DE	**0.517*** (3.89)**	**0.278*** (5.27)**	**0.624*** (5.07)**	**0.565*** (4.26)**
$LLTE_{it-1}$	**0.281*** (4.28)**	**0.313*** (4.05)**	**0.206*** (3.86)**	**0.519*** (3.53)**
W*DE	**0.358** (2.471)**	--	--	--
PIR	**0.326** (2.41)**	**0.385*** (3.82)**	**0.216*** (3.38)**	**0.601*** (3.26)**
PIG	**-0.393*** (-5.27)**	**-0.461*** (-4.16)**	**-0.257*** (-3.95)**	**-0.718** (-2.45)**
PSG	**0.296*** (5.16)**	**0.373*** (4.83)**	**0.216*** (4.67)**	**0.589*** (4.21)**

UL	**-0.168** (-2.38)**	**-0.217** (-2.45)**	**-0.184** (-2.27)**	**-0.401* (-1.93)**
PIP	**0.336** (2.26)**	**0.427*** (4.58)**	**0.385** (2.46)**	**0.812** (2.15)**

Note: * is passing the 1% confidence test, ** is passing the 5% confidence test, * is passing the 10% confidence test, and the t-test result values are in parentheses.**

According to the test results in Table 5, The digital economy has a positive impact on the efficiency of urban greening transformation, and the lagged term of urban green transformation efficiency passed the significance test with a confidence level of 1%, and the test result is significantly positive, indicating that there is also a notable spatial spillover effect between neighboring cities.

5. Discussion

5.1 Discussion of the results of the robustness test for the basic regression

In order to verify the validity of the impact of the drivers of urban green transition efficiency, it is necessary to use the empirical test theory of quantitative economics to test the robustness of the equation and its variables. According to the principle of robustness testing, there are multiple testing methods for robustness testing, and this paper chooses the alternative variables method and the control fixed effects method for testing. The natural logarithm of the city's green GDP per capita is used to replace the city's green transition efficiency; the digital economy index of Chinese cities calculated by "Tencent Research Institute" is used to replace the digital economy index of Chinese cities calculated by the People's Bank of China in this paper; at the same time, this paper also adopts the method of controlling the fixed effects to carry out the stability test, which is mainly to control the fixed effects of each city and the fixed effects of each city. At the same time, this paper also adopts the method of controlling fixed effects to carry out the robustness test, mainly controlling the fixed effects of each city and the interaction effect between city-year variables, and the specific test results are shown in Table 6.

Table 6. results of robustness discussion

variant	substitution of variables acts		lagged term		Shorten data cycle （2015-2021）
	Replacement of the dependent variable	Sample correction method for explanatory variables	lagged term 1	lagged term 2	
DE	0.388* (1.89)	0.412*** (5.47)	0.378*** （3.671）	0.367*** （3.263）	0.489** （2.361）

City-F	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Year-F	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
N	**2630**	**2630**	**2630**	**2630**	**1841**
R^2	**0.45**	**0.41**	**0.39**	**0.42**	**0.44**

Note: * is passing the 1% confidence test, ** is passing the 5% confidence test, * is passing the 10% confidence test, and the t-test result values are in parentheses.**

Based on the above test results: using the natural logarithm of urban green GDP per capita to replace the efficiency of urban green transformation passes the significance level test with a confidence level of 10% and has a positive impact effect, and the results of the other ways of testing pass the significance test with a confidence level of 1%, which fully demonstrates the robustness of the test model and its variables; Due to the use of a fixed-effect model, it is not possible to use the coefficient-fixing method for robustness testing. Considering the actual situation of this study, in addition to robustness testing using the substitution variable method, two other methods, namely lag term testing and shortening the data period, were used for robustness testing. The robustness of the variables and model in this paper is fully demonstrated by the robustness test.

5.2 Discussion of the results of the heterogeneity test for urban differences

Heterogeneity analysis is the content of difference analysis in the empirical test method, focusing on analyzing the differences in the empirical test results due to the differences in policies, environments, influencing factors, and the research object's own factors. Since this paper selects 263 cities with basically similar policies, environments and influencing factors among 348 cities at prefecture level and above in China as the research object. However, differences between different cities still exist. In order to analyze the variability of test results between different types of cities, according to the ranking of Chinese cities released by the Walton Institute of Economic Research in 2022, Chinese cities are distinguished into four tiers based on GDP, namely first-tier, second-tier, third-tier and other cities; and according to the list of China's resource cities released by the State Council, Chinese cities are distinguished into resource-based cities and non-resource-based cities. According to these two kinds of city classification, the heterogeneity test of cities is carried out by utilizing the pre-constructed test model and the basic information prepared beforehand, and the specific test results are shown in Table 7.

Table 7: Heterogeneity test results for different classified cities

Variables	**1-2 tier**	**3rd tier**	**Other cities**	**resource-based**	**Non-resource-based**

	cities	cities		city	cities
DE	0.678*** (4.45)	0.514** (2.38)	0.271* (1.92)	0.681*** (4.67)	0.426** (2.26)
Constant	1.183** (2.47)	0.847*** (4.463)	0.817*** (4.26)	1.162*** (4.78)	0.816*** (4.35)
N	2630	2630	2630	2630	2630
R^2	0.127	0.147	0.203	0.295	0.267
City-F	Yes	Yes	Yes	Yes	Yes
Year-F	Yes	Yes	Yes	Yes	Yes

Note: * is passing the 1% confidence test, ** is passing the 5% confidence test, * is passing the 10% confidence test, and the t-test result values are in parentheses.**

From the above table, it can be clearly seen that the digital economy of tier 1-2 cities and resource cities has a greater impact on the efficiency of green transformation, and the corresponding of other cities will be relatively lower; at the same time, the significance of the impact of the digital economy of tier 1-2 cities and resource cities on the efficiency of green transformation is also higher, and all of them passed the significance test with a confidence level of 1%, while the significance of the corresponding impact of other cities will be lower. The significance of the corresponding impact in other cities is lower, only passing the significance test of 5% or 10%. This paper selects the fixed-effect test model, uses the double-fixed of city and year, re-examines the determined test environment and conditions and heterogeneity test, and clarifies the heterogeneity characteristics of the research subjects.

6. Summary and recommendations

In order to study the impact status of the level of digital economy development on the efficiency of urban green transformation, this paper selects 263 prefecture-level cities in China as the research object, adopts the basic regression model, mediated effect model and spatial Durbin model as the research object, and utilizes the basic data of the research object from 2012-2021, and adopts the SBM model considering energy consumption and non-desired output to measure the green transformation efficiency, and using the measurement results as the dependent variable, six indicators such as digital economy, investment rate in environmental pollution control, per capita value-added share of urban industry, per capita value-added share of urban services urbanization level and the share of investment dedicated to green transformation as the dependent variables, and the level of green technological innovation, industrial structure upgrading and green production efficiency as the mediator variables, we used the combination

method of the basic regression model, the mediator variables model and the spatial Using a combination of basic regression model, mediator variable model and spatial Durbin model, the study empirically examines the impact of driving factors on the efficiency of green transformation in Chinese cities. The study found that: the digital economy index has a positive correlation on the efficiency of urban low-carbon transformation, and the corresponding positive influence coefficient is 0.523, and the influence of the control variables on the efficiency of urban green low-carbon transformation presents differentiated characteristics, among which: the investment rate of environmental pollution control, the per capita value added ratio of urban service industry and the ratio of investment dedicated to green transformation present positive correlation on the efficiency of urban green transformation, and the corresponding influence coefficients are 0.4 and 0.4, respectively. The impact coefficients are 0.437, 0.304 and 0.368, respectively; the ratio of urban industrial value added per capita and the level of urbanization show an inverse correlation with the efficiency of urban green transformation, and the corresponding impact coefficients are -0.412 and -0.276, respectively; among the three intermediary effects, the upgrading of industrial structure has the greatest impact on the efficiency of urban green transformation, with an impact coefficient of 0.673, and the spatial Dubin model tested the spillover effect of digital economy on urban green transition efficiency, with an impact coefficient of 0.517. The findings of this paper have important practical value for the formulation of urban green transition efficiency improvement policies.

Based on the above test results, this paper provides policy recommendations in the following areas.

(1) Actively playing a facilitating role in presenting positively correlated driving factors for urban green transition efficiency. According to the test results of the benchmark regression, in addition to the digital economy, three control variables such as the investment rate in environmental pollution control, the per capita value added share of the urban service industry and the share of investment dedicated to green transformation have a promotional effect on the efficiency of urban green transformation, and the other factors have an inhibitory effect, which promotes the maximization of the integrated role of the driving factors on the efficiency of urban green transformation.

(2) Fully utilize the indirect role of mediating variables on the improvement of urban green transformation efficiency. According to the test results of mediating variables, the green technology innovation level, industrial structure upgrading and green production efficiency have an indirect role in enhancing the efficiency of urban green transformation. Make full use of the three intermediary variables to enhance the efficiency of urban green transformation to achieve optimal results with minimal effort.

(3) Fully utilize the digital economy and its control variables on the heterogeneity of urban green

transition efficiency in cities to promote the sustainable improvement of urban green transition efficiency. According to the results of the heterogeneity test, the rapid and sensitive role of 1-2 tier cities and resource-based cities in enhancing the efficiency of urban green transformation should be increased, while the differentiated strategies for other cities to promote the enhancement of urban green transformation efficiency should be strengthened.

Conflict of Interest

The authors declare no conflict of interest

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