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Digital economy, industrial agglomeration, and green innovation efficiency: empirical analysis based on Chinese data

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ABSTRACT

This study measures and analyzes the spatial characteristics of the relevant indices by constructing an evaluation index system. The SBM-DEA model and Tobit regression model were used to empirically test the influence relationship between digital economy, industrial agglomeration, and green innovation efficiency development. The study results show (1) the development level of China's digital economy, industrial agglomeration and green innovation efficiency shows a heterogeneous character of "high in the east and low in the west" at the spatial level. (2) the positive effect of China's digital economy and diversified industrial agglomeration on the development of green innovation efficiency. (3) Among other influencing factors, trade openness and labor quality have a significant impact on improving the efficiency of green innovation. Therefore, this study puts forward suggestions to strengthen the construction of new infrastructures, correctly guide the collaborative industrial agglomeration, and strengthen the exchange of information among enterprisers.

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KEYWORDS
Digital economy; industrial agglomeration; green innovation efficiency

1. Introduction

With the rapid development of the global economy, the high growth in energy consumption and emissions under prevailing economic development models based on traditional industrial systems have seriously damaged ecological and environmental systems worldwide. It is crucial to coordinate the balance between digital transformation and ecological sustainability (Lynn & Peeva, 2021; Martínez & Alonso, 2018). A green innovation model that balances economic growth and environmental protection, is of key significance for promoting sustainable development and is gradually becoming a common path for innovation transformation in China and other countries around the world (Zhang et al., 2022). In recent years, China has responded positively to the global trend of green and low-carbon development and proactively laid out plans accompanied by an extensive promotion of carbon emission reduction in the international arena. In September 2020, Chinese President Xi Jinping announced via video at the

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75th session of the UN General Assembly held in September 2020 that carbon dioxide emissions would peak before 2030—and that the country would achieve carbon neutrality by 2060. Therefore, how to coordinate economic development and green innovation has become one of the urgent issues to be solved in China and the world at this stage.

At present, global economic development is embracing the "digital economy" represented by digital transformation and the technological paradigm formed by the digital economy also promotes the development and evolution of an industrial innovation paradigm. The 21st century's digital development of industry has given China's national economy a more solid position and more obvious supporting role in digital development (Zhao et al., 2020). In recent years, the scale of China's digital economy has grown from RMB 11 trillion in 2012 to RMB 50.2 trillion in 2022, and its share of GDP has risen from 21.6% to 41.5%, with industrial digitization accounting for as much as 33.6% of the GDP. Furthermore, the 2022 China Digital Economy Development Report (TekSystems, 2022) put forward new requirements for the development of industrial digitalization, pointing out that the industrial agglomeration level of industrial parks should be improved, digital solutions should be developed, and industrial agglomeration should be promoted. In the context of Industry 4.0, digital transformation and ecological sustainability are having a significant impact on advancing industries, companies and regions (Awan et al., 2022; Xu & Zhang, 2020). However, there are development gaps in the economic foundation and industrial resources of various regions; hence, digital technology and its rapid iterative development has created a "digital divide" problem between industries and enterprises. This divide has led to an unbalanced development of digital capture transformation. While promoting the development of industrial agglomeration, the digital economy has had different innovation impacts on the heterogeneous industrial structure system. For example China's built the famous Zhongguancun National Demonstration Zone in Beijing with its development of 16 industrial parks, utilizing many high-tech enterprises. Moreover, the Hefei, Anhui Province has formed a large-scale intelligent voice industry cluster on the back of KDDI China's corporate strengths, which provides ICT solutions to more than 100 countries. These types of industrial agglomeration models can only play a greater agglomeration effect and positive role under adaptable conditions. In the context of the real needs and development of green innovation and digital economy, studying the innovation transformation mode and effective relationships of industrial agglomeration is of great significance.

In summary, in order to effectively improve the efficiency of green innovation and narrow the development gap of regional digital transformation, it is necessary to coordinate the development relationship between the digital economy, industrial agglomeration, and green innovation. This study proposes a theoretical framework based on the social reality of the opportunities and challenges brought by the digital economy to industrial and ecological development, demonstrating the impact mechanisms of the digital economy, industrial agglomeration, and green innovation performance. In addition, the authors used econometric methods to empirically test the relationship between variables and provide empirical support that can effectively develop and improve the efficiency of digital economy, industrial agglomeration, and green innovation. This paper focuses on answering the following questions: Are there regional differences in the digital economy and industrial agglomeration that affect green innovation efficiency? Does the

digital economy and industrial agglomeration contribute significantly to the improvement of green innovation efficiency? Can the digital economy influence the development of green innovation efficiency by supporting industrial agglomeration?

The rest of this paper is organized as follows. Section 2 is a literature review. Section 3 introduces the mechanism of interaction between digital economy, industrial agglomeration and green innovation efficiency and puts forward research hypotheses. Section 4 introduces the model method and constructs the index. Section 5 presents empirical results and discussion. Section 6 is the conclusion and plan for future research.

2. Literature review

The growing concern of the international community regarding ecological issues has caused green innovation to become a hot topic for researchers, world leaders, and civilization as a whole. At present, research on green innovation mainly focuses on the concepts of definition, evaluation index construction, and efficiency measurement. Initially, scholars put forward a series of innovative development-related ideas to study the problem of resolving the contradiction between society, natural resources and the environment (Hall et al., 2003; Oltra & Saint Jean, 2009). Hellström (2007) refers to environmentally sustainable innovation and development as eco-innovation based on the connotation of Schumpeter's innovation theory, which points out that eco-innovation is mainly about replacing the original product with an improved process or with a more environmentally friendly product. Campo and Trio (2022), on the other hand, emphasizes that eco-innovation mainly reflects corporate social responsibility and is a tool adopted by companies to improve the quality and efficiency of product production. Aguilera-Caracuel and Ortiz de Mandojana (2013) defines green innovation as a means of technological improvement, primarily through green product development and management by reducing environmental pollution and increasing resource efficiency.

In-depth research on the connotation of green innovation has measured and evaluated green innovation efficiency evaluation. Heinis et al. (2018) measured the product innovation efficiency of manufacturing companies from the perspective of Internet of Things applications by means of a questionnaire survey. Some scholars have empirically tested the impact of green innovation on green efficiency by dividing innovation into green process innovation and green product innovation (Wong, 2013; Wong et al., 2012). Song et al. (2022) measured the green innovation efficiency of the manufacturing industry based on panel data from 30 provinces in China with numerical measures of R&D inputs and outputs, demonstrating that the clustering of high-tech industries helps promote the green transformation of manufacturing enterprises. Ghisetti and Rennings (2014) measured the efficiency of green innovation and chose to construct a system of evaluation indicators in terms of both energy consumption and environmental pollution, and finally made a distinction between energy-effective and environmentally beneficial innovations based on the conclusions. In terms of indicator construction and models, the DEA-SBM and DEA-RAM models are two typical types of evaluation models that incorporate non-desired outputs such as environmental issues into innovation efficiency. These models have been applied by many scholars (Ghisetti & Rennings, 2014; Tone, 2001). Miao et al. (2021) illustrated the development status and causes of differences in regional green

innovation efficiency in terms of energy and negative outputs. This study was based on the constructed SBM-DEA model (Miao et al., 2021)

To explore effective ways to enhance the efficiency of green innovation, scholars have found that industrial agglomeration is the main growth factor in industrial allocation, which has a relatively close causal relationship with green development (Cheng et al., 2018; He et al., 2022). However, the impact of the digital economy and industrial transformation effects on green innovation efficiency, have been presented from different viewpoints. On the one hand, most studies consider industrial agglomeration as the gateway to green development when the industrial decision makers promote economic development and implement the transformation of industrial goals to accommodate green innovation in economic values (Ren et al., 2019). Aritenang (2021) constructed a concentration model to test the role of high-technology industries in relation to agglomeration economy, using Indonesia as the study area. He found that areas with high industrial intensity promote technological progress and economic growth. Pangarso et al. (2022) argues that in the context of digital development, business managers must harmonize environmental protection and economic efficiency through operating in a green economy. On the other hand, some scholars believe that the relationship between industrial transformation and green development is not purely positive. Hu et al. (2018) found that the influence of industrial agglomeration and green benefits showed an inverted "U" shaped trend. Hanna (2020) pointed out that uneven development of the digital economy can lead to inevitable risk in inequality and relative poverty in some instances, and that modern businesses should take relevant measures to enhance the digital resilience of economic efficiency and environmental protection. Shabir (2022) illustrated that rapid economic globalization can adversely affect environmental protection from the research perspective of financial inclusion.

To summarize, existing research results all provide a realistic basis and theoretical support for this paper to explore how to coordinate the balanced development of digital economy and green innovation through industrial agglomeration. However, the existing research system still has some shortcomings to be supplemented and improved. First, many scholars have proposed that the development of industrial agglomeration will have a certain impact on the economy and environmental protection, but few studies have explored the in depth interaction between the digital economy, industrial agglomeration and green innovation efficiency, thereby neglecting the impact of the two different ways of industrial specialization and diversified agglomeration. Secondly, the measurement of green innovation efficiency only selects a certain region for evaluation and lacks a comparative analysis of the heterogeneity of different regions, which may lead to the lack of universality of the research results. Therefore, on the basis of existing theoretical research, this paper systematically analyzes the interaction relationship among digital economy, industrial agglomeration and green innovation efficiency, and puts forward a research hypothesis based on that analysis. Then, an evaluation index system suitable for this article was constructed using panel data from 31 provinces in China, as well as the spatial impact mechanism of China's digital economy, industrial agglomeration, and green innovation efficiency development – all of which were empirically tested using the

SBM-DEA model and Tobit regression model. This approach reveals key factors and development paths for effectively coordinating economic and ecological sustainable development.

3. Mechanistic analysis and research hypothesis

3.1. Digital economy and green innovation efficiency

As a source of innovation and change in products, business models and industrial patterns, the digital economy plays a key role in promoting green innovation. The gist of green innovation's ecological intentions is to develop new ways to produce products that protect the environment and assist in alleviating damage caused by older processes. First, digital economy enables technological innovation with high efficiency, low cost, and low resource depletion based on the knowledge spillover effect. When industry works with digital economists, optimization and reduction of manufacturing costs can be achieved despite the absence of practices that harm the environment. This type of partnership can continuously improve the construction of the digital infrastructure for ecological environment governance through technological innovation. This requires increasing the frequency of technical innovation through diffusion and optimization of production links that promote the creation of new values requiring lower resource consumption (Kohli & Melville, 2019). Second, the development of the digital economy is supported by the ability of technological innovation to enforce substantial and sustainable development of green technology innovation. Green innovation efficiency reduces environmental pollution and the use of raw materials and energy with the help of technological innovation. In the process of promoting the coordinated development of economic activities and continuous improvement in resource allocation efficiency, the digital economy can effectively stimulate green innovation efficiency based on the kinetic energy of sustainable product production (Thompson et al., 2013).

H1: Digital economy can effectively enhance the level of green innovation and efficiency development.

3.2. Specialized clustering, diversity clustering, and green innovation efficiency

Industrial agglomeration can be divided into specialized and diversified leadership groups according to the type of agglomerated enterprises. Specialized agglomeration refers to agglomeration formed by a certain scale representing a single type of enterprises in a specified geographical space, which is mainly manifested as the convergence of technology-oriented structures. Large-scale professional agglomeration makes the cooperation between the product technology division of labor and the workers cooperation more detailed, which can reduce the cost of green technology and promote the level of green innovation efficiency to a certain extent. However, the specialized clustering and technological convergence of the same type of enterprises are likely to cause the homogenization and mechanization of production methods and operation modes, which may lead to low efficiency of green

innovation. Diversified agglomeration refers to the agglomeration of multiple types of enterprises formed in a specific geographical space, representing the integration of multiple technologies. Through spatial convergence, multiple types of enterprises continuously promote the interactive flow of technological resources. This type of interaction can lead to the convergence and overflow of differentiated knowledge in the process of forming collaborative relationships in manufacturing and transactions. However, the participation of multiple industries in the production of products tends to disrupt the order of market competition when the "crowding effect" occurs. The disruption happens when vicious competition leads to resource scarcity, which could potentially squeeze out the positive external benefits of green innovation efficiency – at least in areas where this type of competition occurs.

H2: Different types of industrial agglomeration forms have different impacts on the development of green innovation efficiency.

3.3. Digital economy, industrial agglomeration, and green innovation efficiency

At present, human society is gradually entering a new stage of development with digital productivity as the main symbol. The digital economy has spawned a number of new industries, technologies and business models. It serves as an engine to drive the optimization and upgrading of traditional industrial institutions (Liu et al., 2022). Thus, industrial clustering driven by the digital economy may deepen the impact on the efficiency of green innovation. First, the digital economy's use of new technologies and Internet applications has caused traditional industries to undergo all-round, full-angle, full-chain transformation. This creates industrial clustering which benefits greatly from the external effects of network synergy (Bertschek et al., 2013). At this point, the knowledge spillover effect was brought into play by forming a circular chain reaction of networked, collaborative development and efficient utilization that continuously promotes green technological progress. Second, the industrial agglomeration empowered by digital economy not only has the spatial advantage of concentration at the geographical level, but also increases the flexibility and science of the division of labor with the support of digital information technology. Both the openness and restrictions of the internet gives full play to the advantages of industrial agglomeration and improves the level of development for green innovation efficiency.

H3: The driving impact of the digital economy can change the path of industrial agglomeration on the efficiency of green innovation.

4. Research design

Based on the above discussion and proposed research hypotheses, this article takes the digital economy and industrial agglomeration as explanatory variables and the green innovation efficiency as explanatory variables. The specific model design and empirical testing protocol are: (1) Variable measurement: Based on panel data measurement, the

development level of the digital economy in the research sample is studied; The SBM-DEA model is constructed to measure the efficiency level of green innovation, and the entropy method is used to measure the level of industrial agglomeration. (2) Regression analysis: Based on the calculated values of each variable, a Tobit regression model is constructed to test the proposed research hypotheses. (3) Empirical result analysis: Use ArcGIS software to visualize descriptive statistics in space and analyze the correlation between variables based on the estimated results; then, the conclusion is drawn out and completed accordingly. The specific settings and data sources of the model are as follows:

4.1. Model construction

4.1.1. Slacks-based measure (based on) data envelopment analysis (SBM-DEA) model

The SBM-DEA model presented in this paper is constructed based on the research of Rashidi and Saen (2015) and Mandal (2010). This model effectively solves the problem of efficiency evaluation under input slackness and non-expected output by factoring in the slack variables within the calculation of efficiency values (Tone, 2001). The study assumes n decision units, each with m input indicators for the input vector X and s_1. The output indicators for the desired output vector are Y^g, and the non-desired output vector is s_2 for the non-desired output vector Y^b. According to the requirements of the SBM-DEA model that considers undesired outputs (Fang et al., 2013), there exists $x_i \in R_m$, $y^g \in R^{s_1}$, and $y^b \in R^{s_2}$. Based on this, the matrix definitions and SBM-DEA models of X, Y^g, and Y^b are constructed in this paper, and their corresponding equations are expressed as:

$$X = [x1, \cdots xn] \in R^{m\times n}$$

$$Y^g = [y^g 1, \cdots y^g n] \in R^{s_1\times n}$$

$$Y^b = [y^b 1, \cdots y^b n] \in R^{s_2\times n} \tag{1}$$

with the objective function GIE, which represent the green innovation efficiency expressed as:

$$GIE = min \frac{1 - \frac{1}{m}\sum_{i=1}^{m}\frac{\bar{s_i}}{X_{io}}}{1 + \frac{1}{s_1+s_2}\left[\sum_{i=1}^{s_1}\frac{s_r^g}{y_{r0}^g} + \sum_{i=1}^{s_2}\frac{s_r^b}{y_{ro}^b}\right]}$$

$$s.t.\ x \geq \lambda X,\ y^g \leq \lambda Y^b,\ y^b \geq \lambda Y^b,\ \lambda \geq 0 \tag{2}$$

λ is the weight vector, and s^-,s^g, and s^brepresent the slack variables of the green innovation inputs, green innovation desired outputs, and non-desired outputs, respectively, in a perfectly decreasing manner and where $0 \leq P^* \leq 1$. For a particular decision cell, if $GIE = 1$ and s^-, s^g, and s^b are all 0, it means that the efficiency is effective. If $GIE < 1$, or if s^-, s^g, and s^b are not all 0, it means that the decision unit is inefficient, and

the inputs and outputs must be improved. These calculations are used to determine the level of development for green innovation efficiency in the study area based on these results.

4.1.2. Tobit regression model

The green innovation efficiency measured using the SBM-DEA model is a discrete truncated value between 0 and 1. Therefore, this paper uses a panel Tobit model (Tobin, 1958) dealing with restricted dependent variables to test the factors influencing the efficiency of green innovation. The formula is shown as:

$$GIE_{it} = \alpha + \beta_1 DIE_{it} + \beta_2 LQ_{it} + \beta_3 STR_{it} + \beta_4 GOV_{it} + \beta_5 EDU_{it} + \beta_6 REG_{it} + \mu_{it} + \varepsilon_{it} \tag{3}$$

where i represents the province, t represents time. DIE_{it} and LQ_{it} represent the core explanatory variables measuring the level of regional digital economy development and the degree of industrial agglomeration, respectively. STR_{it}, GOV_{it}, EDU_{it} and REG_{it} represent other control variables, μ_{it} represents the regional fixed effects that do not vary over time, and ε_{it} is a random disturbance term.

Considering the influence between digital economy and industrial agglomeration development, the interaction model between digital economy and industrial agglomeration is constructed on the basis of Equation 3, i.e., the cross term of the digital economy index (*DIE*) and industrial agglomeration index (*SLQ* and *DLQ*) is introduced into the econometric model as:

$$GIE_{it} = \alpha + \rho DIE_{it} * SLQ_{it} + \beta_2 LQ_{it} + \beta_3 STR_{it} + \beta_4 GOV_{it} + \beta_5 EDU_{it} + \beta_6 REG_{it} + \mu_{it} + \varepsilon_{it}$$

$$GIE_{it} = \alpha + \delta DIE_{it} * DLQ_{it} + \beta_2 LQ_{it} + \beta_3 STR_{it} + \beta_4 GOV_{it} + \beta_5 EDU_{it} + \beta_6 REG_{it} + \mu_{it} + \varepsilon_{it} \tag{4}$$

where ρ and δ represent the coefficients corresponding to the cross terms, and the rest of the symbols have the same meaning as Equation 3.

4.2. Sample selection and data sources

4.2.1. Explanatory variables-digital economy

Drawing on previous studies (Tian & Zhang, 2022), the entropy value method was used to comprehensively calculate and study the level of the regional digital economy development. Moreover, the digital economy development evaluation index system of this paper is constructed from three aspects: digital production, digital innovation, and digital applications, respectively. The details are shown in Table 1.

4.2.2. Explanatory variables-industry cluster

The industrial agglomeration index is an index proposed by Ellison and Glaeser (1997) to measure industrial agglomeration. At present, the main methods to measure the degree of industrial agglomeration are industry concentration (*Concentration Ratio*), the Herfindahl-Hirschman index (*HHI index*), and the locational entropy index (*LQ index*). To validate the research results, this article provides a specialization

Table 1. Evaluation index system of digital economy development level.

Indicators	Specific indicators	Unit
Digital Production	Number of Internet broadband access subscribers	10,000 persons
	Total Telecommunications Business	100 million CNY
	Number of information technology service enterprises	Pieces
	Information transmission, computer services and software industry personnel	10,000 persons
Digital innovation	Number of general higher education schools	Pieces
	High Technology Industry Patents	Items
	Internal expenditure on R&D funds for high-tech industries	10,000 CNY
Digital application	E-commerce sales	100 million CNY
	Internet-related outputs	100 million CNY
	Digital Inclusive Finance Index	/

agglomeration index and a diversification agglomeration index as models to measure the industrial agglomeration level of the research unit.

(1) Specialized agglomeration: To reflect the spatial distribution of regional factors, the LQ index is used to measure the level of industrial specialized agglomeration, and the specific choice is made to construct the location entropy of employees in the information transmission, computer services and software industries to reflect the degree of industrial agglomeration in this paper. The model is shown as:

$$SLQ_{ij} = \left(p_{ij}/p_i\right)/\left(P_j/P\right) \tag{5}$$

where, p_{ij} denotes the employees in industry j in region i; p_i denotes the employees in all industries in region i; P_j denotes the employees in industry j nationwide; P denotes the employees in all industries nationwide. The larger the value of LQ_{ij}, the higher the degree of industry concentration in the region.

(2) Diversified agglomeration: In order to compare the gap of industrial agglomeration between different regions, the Herfindahl (HDI) index is used to measure the level of industrial diversified agglomeration. The specific calculation is expressed as:

$$DLQ_{ij} = \frac{1}{\sum_{i=1}^{n} S_{ij}^2} \tag{6}$$

where n denotes the number of industries and S_{ij}^2 denotes the proportion of the output value of industry j in region i to the GDP of region i. The industry data are obtained from the China Statistical Yearbook on the output value of the tertiary industry. The larger the value of the HDI index ($DLQ_{i\,j}$) is, the smaller the degree of diversification agglomeration in the region, and the smaller the $DLQ_{i\ j}$ is, the larger the degree of diversification agglomeration in the region.

4.2.3. Explained variables-green innovation efficiency

Before applying the SBM-DEA model to measure the green innovation efficiency of the research unit, it is necessary to clarify the research-related input indicators, output indicators and non-desired output indicators. (1) Input indicators are mainly personnel input, capital input and energy input (Young, 2003). This paper presents the full-time equivalent of R&D personnel in industrial enterprises above the scale as the labor input indicator. The capital input selects R&D internal funding expenditure, the environmental pollution control investment, and the energy conservation and environmental protection expenditures as the

measurement indicators. And the total regional energy consumption is selected as the resource input indicator (Tone, 2001). (2) Expected output indicators mainly include technical output and product output of green innovation activities, and the number of green invention patents granted, technology market turnovers, and new product sales revenue are chosen as expected output indicators to measure green innovation efficiency (Bronzini & Piselli, 2016; Chen et al., 2021; Spanos et al., 2015). (3) Non-desired output refers to minimizing environmental pollution while maximizing desired output. Total industrial wastewater emissions, total industrial sulfur dioxide emissions, and sulfur dioxide emissions are selected as non-desired output indicators to measure the efficiency of green innovation, respectively (Zheng et al., 2021).

4.2.4. Control variables

To analyze the relationships more accurately between the digital economy, industrial agglomeration and green innovation efficiency. Based on other studies, the authors selected control variables that may affect green innovation efficiency. The control variables are:(1) Industrial structure (*STR*): The proportion of the tertiary industry's added value to the regional GDP is selected to measure this indicator (Zhu et al., 2019). (2) Government support (*GOV*): Reasonable government input can improve the capital investment of enterprises and promote the optimal allocation of resources. The choice of government financial science and technology expenditure affects the total energy factor productivity (Wang et al., 2021). (3) Workforce quality (*QUA*): Human resources are the main means of implementing innovation activities. The number of years of education per capita in the region is the workforce quality indicator (Tong et al., 2020). (4) Degree of trade openness (*OPE*): The openness level of foreign investment has an important impact on regional green development. In this paper, the total imports and export of foreign-invested enterprises is used to reflect the degree of regional trade development.

4.2.5. Data source

Considering the availability and authenticity of data, authors were selected to represent the panel data of 31 Chinese provinces (autonomous regions and municipalities directly under the central government) from 2011 to 2020 as the research object. Among them, the data for digital economy-related indicators came from the China Statistical Yearbook (2012–2021) and China Science and Technology Statistical Yearbook (2012–2021). The data for industrial agglomeration indicators is in the China Industrial Statistical Yearbook (2012–2021), and the data used for green innovation efficiency indicators are in the China Environmental Yearbook (2012–2021) and China Energy Statistical Yearbook (2012–2021). The missing data were supplemented by using provincial and municipal statistical yearbooks and statistical bulletins aimed at improving national economic and social development. The data of green invention patents obtained from the Chinese Innovation Research Database (CIRD) sub-database in the Chinese Research Data Services (CNRDS) database.

Table 2. Results of descriptive statistics of variables.

Variable		N	Max	Min	Mean	sd	Median
Explained variables	EFF	310	1	0.026	0.374	0.311	0.26
	DIE	310	0.982	0.077	0.371	0.174	0.335
Explanatory variables	SLQ	310	1.831	0.762	1.006	0.168	0.965
	DLQ	310	3.846	0.373	0.84	0.434	0.753
Control variables	OPE	310	59207.053	0.009	6002.099	1276.636	1276.636
	QUA	310	5613	1082	2608.232	812.105	2424
	STR	310	62550.8	346.1	12053.371	10988.548	8551.7
	GOV	310	1168.79	3.38	123.823	158.92	61.115

5. Empirical results and analysis

5.1. Descriptive statistics

As shown in the results in Table 2, the green innovation efficiency(*EFF*) development levels of 31 Chinese provinces (autonomous regions and municipalities directly under the central government) vary widely across different periods and regions. There are obvious disparities in the level of digital economy development between regions, but the level of digital economy economic development was relatively stable in the sample cycle. In terms of industrial agglomeration, both specialized agglomeration and diversified agglomeration levels are higher in the sample period, but the overall fluctuation level of diversified agglomeration is greater than that of specialized agglomeration. In terms of control variables, the changes in regional degree of trade OPE, GOV and STR development during the sample period are more obvious. Among them, OPE changes most significantly, which indicates that there are large differences in the total import and export of regional foreign-invested enterprises, government financial science and technology expenditures and tertiary industry development during the sample period due to factors such as the level of regional and social development. On the contrary, the change in education development has been relatively smooth, indicating that the change in the number of years of education per capita in the region during the sample period is less volatile and the quality of the workforce is high in all cases.

5.2. Analysis of spatial pattern characteristics

To explore the relationship between variables more systematically, the model calculation results of digital economy index, industrial agglomeration location entropy index, and green innovation efficiency index of 31 Chinese provinces (autonomous regions and municipalities directly under the central government) are visualized in a hierarchical manner with the help of ArcGIS Release 10.2 software to visually present the spatial heterogeneity characteristics of regional development. Specific changes are shown in Figure 1 and 2.

In general, the development of China's digital economy, industrial agglomeration, and green innovation efficiency levels vary greatly by region and can change significantly. Most changes show both synergistic development and divergent characteristics among the dimensions, but overall spatial differences dominate. In 2015 and 2020, these provinces showed a path of divergence from the eastern to the central and western parts of China in decreasing order. The top 10 regions were Beijing, Tianjin, Shanghai, Jiangsu, Zhejiang, Chongqing, Guangdong, Jilin, Hunan and Hainan, among which,

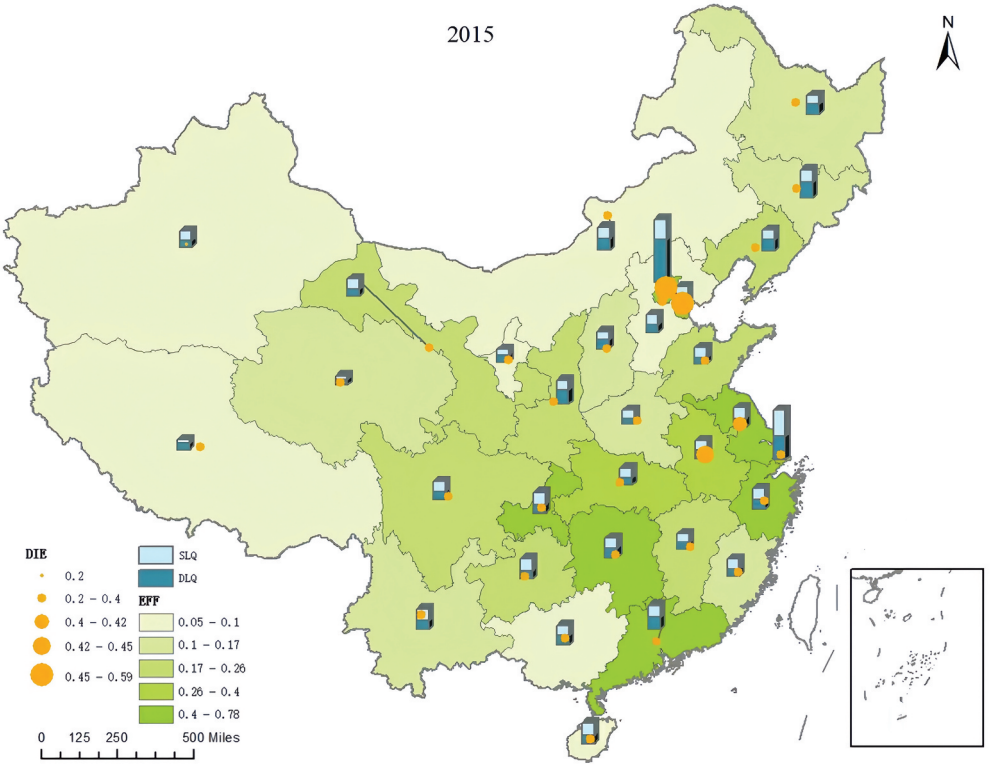

Figure 1. 2015 Spatial Development Patterns of China's Digital Economy, Green Innovation Efficiency and Industrial Clustering.

Beijing, Tianjin, Shanghai, Guangdong and Chongqing had the highest efficiency of green innovation with input-output combinations. Western regions such as Inner Mongolia, Tibet, Ningxia and Qinghai had lower levels of green innovation efficiency development, all of which were lower than the national average, forming a clear gap between the western and eastern regions – hence the expression: "high in the east and low in the west." In terms of industrial agglomeration, regional specialization in China is mainly a "core-edge type" spatial differentiation centered on Beijing and Shanghai. Unlike the obvious divergent characteristics of green innovation efficiency and digital economy development, a small gap can be found in the levels of specialization outside of Beijing and Shanghai, creating a relatively balanced synergistic development and spatial divergence in time and space dimensions.

5.3. Analysis of the results of panel Tobit estimation

Based on the multiple combinations of explanatory variables and control variables, the Tobit panel models shown in Equation 2 and Equation 3 were regressed, and a total of four restricted Tobit panel models and five unrestricted Tobit panel models with the introduction of cross terms were set up. The specific results are shown in Tables 3 and 4.

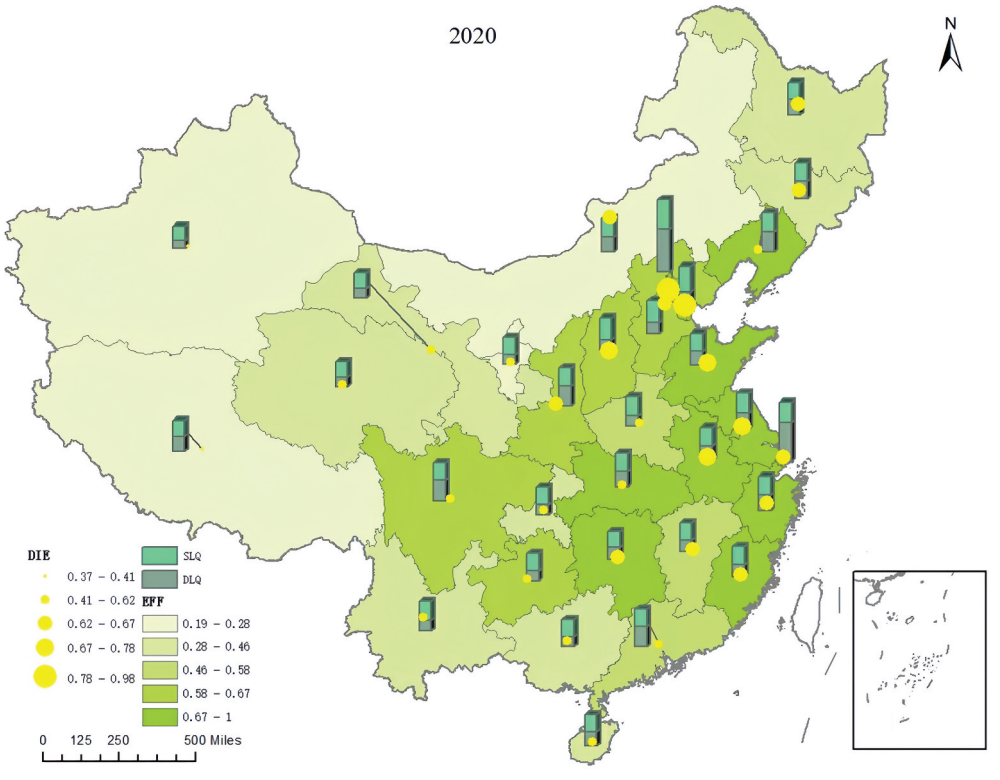

Figure 2. 2020 Spatial Development Patterns of China's Digital Economy, Green Innovation Efficiency and Industrial Clustering.

5.3.1. Basic regression empirical results

In Table 3, the results of model (1), (3), and (4) all show that the digital economy passes the significance test at the 1% level and is positively correlated with green innovation efficiency, indicating that the development of the digital economy can significantly contribute to the development level of green innovation efficiency, which verifies research Hypothesis 1. The key to green innovation development is to balance economic growth and environmental protection. On the one hand, the digital economy integrates with the traditional economy through the Internet, big data, cloud computing and other emerging technologies, forming a more open and transparent market environment. This new accuracy reduces production and transaction costs, achieving a more efficient and effective economic level and economic growth rate in the construction of the modernized economic system. On the other hand, the application of a series of modern technological means and core technologies in the process of digital economy development further promotes the expansion of the scope of innovation resource allocation and improves resource allocation efficiency, reduces the negative impact of economic growth on environmental development, and ultimately realizes the improvement of green innovation efficiency in industries and regions.

The regression results in models (2), (3), and (4) showing that industrial specialization and diversification agglomerations have positive effects on green innovation efficiency (the smaller the DLQ index, the more concentrated the industrial diversification

Table 3. Basic regression empirical results.

	Models			
Variables	(1)	(2)	(3）	(4)
DIE	0.722***(7.948)		0.928***(10.428)	0.734***(8.149)
SLQ		0.246*(1.802)	0.385***(3.018)	0.199*(1.687)
DLQ		−0.142***(−2.589)	−0.037(−0.73)	−0.153***(−3.084)
OPE	0.311***(5.9770	0.259***(4.371)		0.322***(5.921)
QUA	0.276***(3.344)	0.586***(5.267)		0.404***(3.957)
STR	0.029 (0.42)	−0.145(−0.729)		0.008 (0.109)
GOV	0.201 (1.428)	0.84***(3.162)		0.26*(1.836)
Cons	−0.071***(−2.036)	−0.057(−0.512)	−0.327***(−3.177)	−0.192**(−2.067)
LR	120.498***	148.472***	133.416***	209.374***
N	310	310	310	310

Statistical significance: *** = 1%, ** = 5%, and * = 10% levels with t-statistic in parentheses.

Table 4. Introduction of cross term empirical results.

	Models				
Variables	(1)	(2)	(3)	(4)	(5)
DIE	0.868***(4.44)	0.674***(5.087)	0.63***(4.661)	0.445**(2.055)	0.865***(8.12)
SLQ		−0.402***(−3.502)			
DSLQ	−0.109***(−0.697)	0.672***(7.712)		0.478**(1.985)	
DLQ			−0.183***(−2.271)		
DDLQ			−0.131*(1.124)	−0.243***(−2.584)	−0.119***(−2.014)
OPE	0.319***(6.082)	0.334***(5.976)	0.356***(6.58)	0.297***(5.609)	0.321***(6.259)
QUA	0.305***(3.327)	0.304***(3.183)	0.445***(3.183)	0.333***(3.558)	0.365***(3.954)
STR	−0.4**(−2.235)	0.053(0.767)	0.03(0.439)	0.004(0.054)	−0.413** (−2.403)
GOV	0.678***(2.798)	0.16(1.104)	0.193(1.377)	0.272*(1.913)	0.714 ***(3.001)
Cons	−0.061(−1.569)	0.329***(3.594)	0.009(0.142)	−0.086**(−2.196)	−0.083**(−2.13)
LR	204.77***	197.269***	207.802***	206.601***	208.324***
N	310	310	310	310	310

Statistical significance: *** = 1%, ** = 5%, and * = 10% levels with t-statistic in parentheses.

agglomeration), and the specialization agglomeration passes the significance test. However, model (3) has not passed the test, indicating that different industrial agglomerations will have different effects on green innovation efficiency, which verifies research hypothesis 2. The digital economy and specialization agglomeration in model (3) pass the significance test at the 1% level, and the positive effect of the digital economy on the green innovation efficiency is the most significant. The reason why diversification agglomeration did not pass the significance test may indicate the presence of a covariance relationship with digital economy and specialization agglomeration. This indicates a strong correlation between the digital economy and specialization agglomeration on green innovation efficiency only under the influence of a digital economy, with specialization agglomeration and diversification agglomeration. The results in model (4) show that the digital economy, specialization agglomeration and diversification agglomeration, in conjunction with other control variables, form three explanatory variables that have a positive effect on green innovation efficiency. The effects of control variables can change the path of influence for diversified agglomerations focusing on green innovation efficiency within the context of the digital economy. This brings into play favorable conditions created by diversified agglomeration for technological innovation and achieves green innovation efficiency growth.

From the regression results of the control variables in models (1), (2), and (4) the degree of trade openness and labor quality have a positive correlation on the development of green innovation efficiency. Trade openness and labor quality allows foreign investment to bring advanced knowledge, technology, management experience, and production industry to a certain extent, so that enterprises in the region can learn, imitate, and innovate at a close distance, which enhances their own green innovation efficiency. A higher level of education among the population can increase the importance of environmental protection and promote the development of green innovation efficiency. Government investment can have a positive relationship on green innovation efficiency under the combined effect of digital economy and industrial agglomeration, indicating that local governments may hasten the development level of green innovation efficiency through subsidies and investment in green innovation of enterprises, thereby promoting infrastructure construction. However, no obvious linear correlation exists between industrial structures and green innovation efficiency development. This indicates that the current development of tertiary industries in China is not sufficient to achieve greater marginal output benefits for inputs and outputs and has not yet formed a situation that guides the optimal allocation of regional input factors and output benefits.

5.3.2. Introducing cross-term regression empirical results

According to the constructed Equation 2 and Equation 3 the cross terms of digital economy and industrial agglomeration (specialized agglomeration and diversified agglomeration) were introduced and Tobit regression was performed. The obtained results are shown in Table 4.

The cross-sectional regression models in Table 4 (Models (1)-(5)) indicate that the digital economy has a significant positive effect on the development of green innovation efficiency, i.e., digital economic development can promote the improvement of the green innovation efficiency level, which is consistent with the results of the test Hypothesis 1 obtained in Table 3. The results of model (1) show that when the digital economy and specialization agglomeration intersect, the influence of specialization agglomeration on green innovation efficiency will be weakened and may even inhibit the development of green innovation efficiency. This indicates that the digital economy will lead to the convergence of knowledge within the industry due to information sharing and resource network integration of the industry, which will easily cause a free riding behavior of green innovation, which is not conducive to the improvement of green innovation efficiency. However, the coefficient of the cross term between specialization agglomeration and digital economy in models (2) and (4) is positive and passes the significance test, indicating that the condition for specialization agglomeration to play a positive role has a certain critical point. The results of model (3), (4), and (5) show that the intersection of digital economy and diversification agglomeration will promote the development level of green innovation efficiency, since all of them passed the significance test at different degrees, which verifies research Hypothesis 3. This shows that digital economy can integrate information through big data and effectively improve the efficiency of industrial green technology research and development. To a certain extent, the digital economy effectively solves problems such as vicious competition or violation of rules and laws that support fair and cordial competition in the market generated by diversified agglomeration, providing the advantages of industrial agglomeration, thereby improving the development level of green innovation efficiency.

6. Discussion and conclusions

The main conclusions of the thesis study are as follows: (1)China's digital economy is developing rapidly, but the overall level is low to medium, and regional development gaps still exist. Green innovation efficiency shows a steady growth, but regional differences are still obvious, and regional spatial development characteristics show a stepwise spatial development from east to west. Regional industrial agglomerations have obvious "core-edge" development characteristics, and the overall level of diversified agglomeration is higher than that of specialized agglomeration. (2)The development of digital economy has an obvious positive impact on green innovation efficiency and can promote the improvement of regional green innovation efficiency. The influence of specialized agglomeration on green innovation efficiency shows an inverted "U" shape, and under the cross-effect of digital economy, specialized agglomeration may inhibit the development of regional green innovation efficiency. However, diversification agglomeration will continue to promote the level of green innovation efficiency, and the cross-effects with digital economy will deepen the positive impact of diversification agglomeration. In addition, the level of foreign investment and the education level of residents also positively influence the enhancement of regional green innovation efficiency to some extent, and the role of government investment is influenced by the cross-effect of digital economy and industrial agglomeration.

These research findings provide the following policy insights on how to use digital transformation to promote industrial structure upgrading and green innovation: First, the government should promote digital industrialization and digitization of industries. To ensure the benefits of digital economics, industrial agglomeration, and green innovation, the construction of new infrastructure must be accelerated. This infrastructure includes 5 G, an industrial Internet, and blockchain (Luo et al., 2023). Accelerating the integration and penetration of information technology in industries requires a continuous promotion of the digital transformation of traditional industries, as we strive to make the digital economy an effective way to promote the optimization of China's industrial structure, while enhancing the sustainable development of green innovation. Second, it is reasonable to guide the formation of synergistic agglomeration among industries and create a good environment for collaborative innovation among enterprises. Industrial participants should hasten the cultivation of new industries and new models based on digitalization, create a green and sustainable development chain between upstream and downstream industrial chains through information technology, optimize the industrial structure, give full play to the overflow advantages of agglomeration, and accelerate green transformation. Finally, enterprises should strengthen information exchange and technology sharing with diversified subjects, continuously attract foreign investment to promote integration and optimal allocation of innovation resources, accelerate the market transformation rate of green innovation technologies (Amore & Bennedsen, 2016), fully stimulate the spillover effect of the digital economy on diversified agglomeration, and enhance the efficiency of green innovation.

The significance and potential marginal contributions of the paper's research are mainly as follows: (1) Based on hypothesis testing and empirical analysis, the authors provide a new analytical framework, revealing the correlation between digital economy, industrial agglomeration and green innovation efficiency development, which complements the

research in related fields. (2) The development levels of digital economy, industrial agglomeration and green innovation efficiency are comprehensively measured by an improved model. This article illustrates the gaps and spatial differences in the development of each regional index and effectively verifies the causal effects of digital economy development, as well as industrial agglomeration structural differences on green innovation efficiency. (3) The development of industrial agglomeration and green innovation efficiency in the context of the digital economy is explored in depth, responding to the international trend of industrial digitization and sustainable development, and providing references for effective policy implementation in different national contexts.

Finally, it should not be overlooked that due to the limitation of research data availability, this paper only examines the research content at the provincial level, which may not be able to fully reflect the development status and regional differences of digital economy, industrial agglomeration and green innovation at the city level. Therefore, future research can investigate the issue of the digital economy and industrial agglomeration's intersection effect on green innovation efficiency in depth and explore which digital elements can better promote the spillover of agglomeration dividends among regions in order to give full play to the cross-linkage effect of digital economy and industrial agglomeration.

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