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Article

Analyzing the Efficiency and Optimization Strategies of Rural-Urban Integration Driven by Digital Economy Based on Spatial Econometric Models

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Abstract: With the wide application of big data, cloud computing, artificial intelligence and other technologies in the economy and society, the digital economy has become an important engine to lead profound social change and promote high-quality economic development. This paper makes a deep inquiry into the efficiency of urban-rural integration driven by digital economy, measures the efficiency of China's digital economy and urban-rural integration through the entropy method, and analyzes the evolution of the two by using the kernel density estimation method. On this basis, a spatial econometric model was constructed to analyze the effect of digital economy on urban-rural integration efficiency. The study shows that during the period of 2015-2024, the digital economy development index of China as a whole and each province has increased, showing a trend of "from high to low" from east to west. The urban-rural integration efficiency as a whole shows an upward trend, with the eastern region far exceeding the central and western regions, and from the source of differences, inter-group differences are the main source of variability in urban-rural integration efficiency. In addition, the development of digital economy can narrow the gap between urban-rural integration efficiency in local and neighboring provinces, and there is regional heterogeneity in this effect. This paper lays a theoretical foundation for the design of digital economy-driven urban-rural integration efficiency optimization strategies.

Keywords: digital economy; urban-rural integration efficiency; entropy method; kernel density estimation; spatial econometric modeling

1. Introduction

In the twenty-first century, in order to resolve the "three rural issues" and narrow the gap between urban and rural areas, China has implemented an in-depth strategy of urban-rural coordination and urban-rural integration, effectively promoting a new historical stage in China's urban-rural relations. However, in practice, the development path of "urban-centered and growth-oriented" has not changed fundamentally, and China still has outstanding problems such as the massive loss of rural capital factors, insufficient subsidies to agriculture, and relatively slow improvement of urban-rural integration level [1-4]. The unequal status of rural and urban development has become the key reason for the current unbalanced urban-rural development and inadequate rural development [5]. China's high-quality development urgently needs to establish a new type of urban-rural relationship that is equal and mutually beneficial, and to promote the synergistic development of urban and rural production and life, public services, and ecological environment [6]. Based on this, China has proposed the strategic goal of "giving priority to the development of agriculture and rural areas, establishing and improving the institutional mechanism and policy system for the integrated development of urban and rural areas, and accelerating the modernization of agriculture and rural areas in accordance with the general requirements of industrial prosperity, ecological livability, civilized countryside, effective governance, and affluent living", which clearly defines that rural areas are on the same level of strategic position as the urban areas.

Urban-rural integrated development is to take the city and the countryside as an organism, and the key lies in narrowing the income gap between urban and rural areas, driving the two-way flow of urban and rural factors, transforming the dual structure into a unitary structure, and ultimately realizing the free flow of urban and rural factors and the balanced allocation of public resources [7-8]. In order to target effective measures and grasp the driving mechanism of promoting urban-rural integration, scholars have explored the impact of digital development level, digital economy, information technology and other factors on the efficiency of urban-rural integration.

The concept of "digital economy" was first proposed in 1996 by Don Tapscott, a famous new economist, in his book "The Digital Economy", which describes the Internet era as a revolutionary phenomenon in which new types of social relations of production are formed along with the rise of the Internet [9]. Since the 21st century, the digital economy has shown vigorous development, attracting more and more scholars to devote themselves to this research.Carlsson, B (2004) argues that the core of the digital economy is the deep integration of communication technology and information and a series of new technological forms resulting from it, which are prompting an unprecedented transformation of the traditional mode of production and business model [10]. Kolomiyec, H and Hlushach, Y (2017) argued that the digital economy improves the efficiency of information exchange, breaks the spatial limitations with the consumer market, allows companies of different sizes to form a competitive advantage and create a scale effect, but it also results in the reduction of the demand for low and medium-skilled workers in some industries in developed countries, which makes the economy of part-time jobs increasingly hot, which is not conducive to the stabilization of incomes and national economic development [11]. Acemoglu, D and Restrepo, P (2018) found that the digital economy can optimize the allocation of resources, and its rapid development breaks the time and space limitations, reduces the geographic location constraints on the allocation of labor factors, and improves the efficiency of resource allocation [12].

It is also important for scholars to believe that the digital economy is based on Internet technology and involves a wide range of economic activities, such as Internet platform services and data-driven business, which intersects with the information economy and the network economy, but also has its own uniqueness, emphasizing the role of data as a key production factor [13-15]. Domazet, I et al (2018) stated that the digital economy is an economy based on digital technologies, mainly using information technologies, applications and telecommunications in all economic areas of internal activities, and also the digital economy is a knowledge economy because it is essentially a social whole based on professional and market knowledge, creativity and innovation [16]. Stavytskyy, A et al. (2019) suggested that the digital economy is more than just relationships regulated by the Internet, cellular communications and ICT, it transforms business interactions, speeds up the process of various transactions, overcomes market access barriers, removes spatial constraints and creates alternative business platforms [17]. Yakimova, V and Khmura, S (2023) found that uneven regional development of the digital economy exacerbates imbalances in the scale of human capital and digital production in the digital economy, while intra-regional differences in the degree of specialization of the business sector and the availability of digital technologies for the production of services lead to differences in the use of opportunities in the digital economy [18]. Du, D and Jian, X (2025) studied the impact on economic growth from two dimensions of digital technology innovation and digital application innovation, and found that it can contribute significantly to economic growth, and with the improvement of the institutional environment, the digital technology innovation shows a marginal incremental effect, while the digital application innovation shows a U-shape characteristic [19].

With the continuous acceleration of the urbanization process, capital, labor and other factors of production continue to gather from the rural areas to the city, the drawbacks of the dual structure of urban and rural areas are becoming increasingly obvious, and how to better coordinate the relationship between urban and rural areas is the focus of attention of scholars at present [20-22]. In this regard, scholars at home and abroad have carried out extensive research on the efficiency of urban-rural integration from different dimensions and perspectives. Song, F et al. (2014) explored the system and welfare in developing countries and found that the urban-rural dualism is the cause of the weak correlation between the urban and rural management systems, and the existence of bias in the perspectives of the management systems of the urban and rural areas, and at the same time, there is a large difference in the distribution of the welfare in the process of development between urban and rural areas. It shows a serious bias in favor of the urban phenomenon, widening the gap between urban and rural construction and leading to a serious imbalance in economic development [23]. Pijpers, R et al. (2016) explored the system and welfare status quo in foreign developed countries, from which it was found that by unifying the management system, according to the urban welfare standards, and improving the rural welfare treatment from various aspects such as pension, education, medical care and so on can effectively promote the coordinated and integrated development of urban and rural areas [24]. According to Lichter, D and Ziliak, J (2017), the urban-rural divide is widening as never before in the United States, with the increasing mobility of capital, labor, population, information, ideas, and materials, which has led to the blurring of traditional urban-rural boundaries, and he viewed the urban-rural dichotomy as a conceptual and practical obstacle because it is both underdeveloped and unable to share political and economic benefits, and that urban-rural integration is essentially a species of interdependence rather than a clear line separating rural and urban areas [25]. Zhou, J et al. (2020), in the context of China's implementation of the rural revitalization strategy, attempted to explore its impact on the efficiency of urban-rural integration development from the factor pathways of labor, land, capital, industry and transportation [26].

The wide application of digital technology has given birth to the concept of mutual promotion and integration of social community, which provides a new program for promoting the integrated development of urban and rural areas, and has a significant role in amplifying the surplus value of rural areas, diluting the characteristics of urban and rural areas' territoriality, and dissolving the barriers of urban and rural cultural perceptions, which can effectively correct the imbalance between urban and rural areas [27-30]. In this regard, scholars have discussed the efficiency of urban-rural integration driven by the digital economy from different perspectives. Zhao, J and Gong, Y (2020) pointed out that the digital economy helps the digital transformation of agriculture and accelerates the digital construction of agricultural modernization. The digital economy provides intelligent tools and platforms for agricultural production, and through satellite remote sensing, drone monitoring and other technologies, it is possible to obtain real-time information on the agricultural production environment and crop growth, and realize precision agriculture and intelligent agriculture [31]. Bürgin, R et al. (2022) examined how knowledge workers in the Swiss region have achieved urban-rural integration through digital technology, because of modernized infrastructures, urban-rural linkages have never been closer, and technological developments have strengthened the links between the city and the countryside through digitization [32]. Li, Z et al. (2022) concluded that the digital economy, with its high substitutability, permeability, and universality, is transforming the logic of division of labor, optimizing the allocation of resources, and promoting the integration of urban and rural factors, which plays an important role in the construction of a new type of economy, helps to improve the relationship between urban and rural areas, and promotes the rapid development of urban-rural integration [33]. Wang, Y et al. (2023) empirical test found that there is a significant imbalance in the development of China's digital economy, showing a gradient phenomenon in which the development level of the eastern region is higher than that of the central region, and the central region is higher than that of the western region, and the efficiency of urban-rural integration fluctuates and exhibits geographic differences, in which the level of urban-rural integration in the eastern region is higher than that in the western region, and the digital economy greatly promotes the efficiency of urban-rural integration, but there are significant differences between different regions and different The digital economy greatly promotes the efficiency of urban-rural integration, but there are significant differences between different regions and different dimensions [34]. Jia, X et al. (2025) argued that the combination of digital economy and various industries spawned new industries, provided new jobs for urban and rural surplus laborers, and optimized the allocation of labor resources, in which digital inclusive finance reduces the cost of rural financing, and injects capital into the development of rural industries [35]. Lu, Y et al. (2025) explored the impact of digital economy on urban-rural integration by using a two-way fixed effects model, a mediated effects model and a spatial Durbin model, and found that the digital economy further promotes the efficiency of urban-rural integration by indirectly optimizing the allocation factors of labor, capital, land, technology and information [36]. Zhang, L et al. (2025), from an agricultural perspective, found that the digital economy promotes integrated urban-rural development by driving High Quality Agricultural Development (HQAD), thus suggesting that rural areas need to invest in digital infrastructure and create an environment conducive to the application of digital technologies to promote urban-rural integration [37].

Summarizing the above literature, it is found that academic research on digital economy and urban-rural integration is still in the development stage, and the relevant research results are relatively abundant. Existing literature mostly focuses on the impact of population, industry, land, public services, financial benefits and other factors on urban-rural integration development, but seldom incorporates the digital economy into the factors influencing the efficiency of urban-rural integration; secondly, the research on the digital economy on urban-rural integration development is at the theoretical level, and seldom adopts spatial econometrics modeling to empirically study the intrinsic mechanism of the digital economy on the efficiency of urban-rural integration and the mechanism of its impact.

In this paper, the index evaluation system of digital economy index and urban-rural integration efficiency are constructed respectively, taking the panel data of 30 provincial-level administrative regions in China from 2015 to 2024 as an example, and the entropy method is applied to determine the weights of the indexes to realize the measurement of the two. On this basis, using the kernel density estimation method, the spatial and temporal evolution trends of the digital economy and urban-rural integration efficiency are analyzed. In order to further explore the impact of digital economy on urban-rural integration efficiency, this paper constructs a spatial econometric model, analyzes the spatial effect between the two, and conducts a regional heterogeneity test, and proposes an optimization strategy for urban-rural integration efficiency based on the conclusion.

2. Study of trends in the spatial and temporal evolution of the digital economy and the efficiency of urban-rural integration

This chapter applies the entropy and kernel density estimation methods to measure the level of digital economy development and the efficiency of urban-rural integration in 30 provincial-level administrative regions in China, respectively, from 2015 to 2024, and to explore their spatio-temporal evolution trends.

2.1. Research methodology

2.1.1. Entropy method

Entropy method [38] is a multi-criteria decision-making method based on the information entropy theory, which can be used to evaluate and rank multiple indicators or decision-making programs, and can objectively and scientifically determine the weights of different indicators so as to avoid the influence of subjective factors on the evaluation results. The specific calculation steps are as follows:

(1) Data standardization:

Positive:

$$x_{ij}{}' = \frac{x_{ij} - \min\left\{x_{1j}, \cdots, x_{nj}\right\}}{\max\left\{x_{1j}, \cdots, x_{nj}\right\} - \min\left\{x_{1j}, \cdots, x_{nj}\right\}} \tag{1}$$

Negative:

$$x'_{ij} = \frac{\max\left\{x_{1j}, \cdots, x_{nj}\right\} - x_{ij}}{\max\left\{x_{1j}, \cdots, x_{nj}\right\} - \min\left\{x_{1j}, \cdots, x_{nj}\right\}} \tag{2}$$

(2) Determine the share of the j indicator in the indicator under year i, calculated as:

$$P_{ij} = \frac{x_{ij}}{\sum_{i=1}^{n} x_{ij}} \tag{3}$$

(3) Determine the weight of the j th indicator, calculated as:

$$e_j = -\frac{1}{\ln(n)} \sum_{i=1}^{n} p_{ij} \ln\left(p_{ij}\right) \tag{4}$$

(4) Determine the coefficient of variation for the j th indicator, calculated as:

$$d_j = 1 - e_j \tag{5}$$

(5) Determine the weight of the j th indicator, calculated as:

$$w_j = \frac{d_j}{\sum_{j=1}^{m} d_j} \tag{6}$$

(6) Determination of the Composite Development Index (CDI), as specified in the formula:

$$U = \sum_{j=1}^{n} \left(W_{ij} \times x_i^{*}\right) \tag{7}$$

2.1.2. Kernel density estimation

Kernel density estimation [39] is to infer the distribution of the overall data with a limited number of samples, and the nature of the data distribution, such as the aggregation area and distribution pattern of the data, can be obtained through the weighted average to eventually form a continuous kernel density estimation curve. The specific formula is as follows:

Let $\left(x_1, x_2, x_3, \cdots\cdots, x_n\right)$ be a sample of n points that are independently and identically distributed, and whose probability density function is f, whereupon the estimation formula is:

$$f_h(x) = \frac{1}{n}\sum\nolimits_1^n K_{h(x-x_i)} = \frac{1}{nh}\sum\nolimits_{i=1}^n K\left(\frac{x-x_i}{h}\right) \tag{8}$$

where x_i denotes independent identically distributed observations, K is the kernel function, and h denotes the bandwidth, which is generally chosen to be smaller to ensure higher accuracy.

Common kernel density functions include uniform kernel function, triangular kernel function, gamma kernel function and Gaussian kernel function. Since the prediction result of Gaussian function is in probabilistic form, smoother and quicker to calculate, this paper adopts Gaussian kernel function for estimation and analysis, as shown in the following equation:

$$f_h(x) = \frac{1}{N}\sum_{n=1}^{N}\frac{1}{\left(2\pi h^2\right)\dfrac{D}{2}}\left\{-\frac{\left\|x-x_i\right\|^2}{2h^2}\right\} \tag{9}$$

2.2. Measurement of the level of development of the digital economy and analysis of the evolution of the situation

2.2.1. Measurement of the level of development of the digital economy

(1) Construction of digital economy indicator system

This paper argues that the development of digital economy depends on the “four pillars”, namely, the continuous improvement of digital foundation, the continuous optimization of digital environment, the extensive expansion of digital applications and the continuous promotion of digital innovation. On the basis of synthesizing scholars' research results and following the basic principles of selecting indicators such as scientificity and comparability, this paper selects a total of 40 key variables in four dimensions and applies the entropy method to determine the weights of the indicators, and then constructs the evaluation system of China's digital economy development index indicators as shown in Table 1.

Digital Infrastructure (A) provides infrastructure guarantees for the digital economy, consisting of 10 indicators including basic network facilities (A_1) and network application resources (A_2). This includes the length of optical cable lines (A_{11}), the length of long-distance optical cable lines (A_{12}), the number of mobile phone base stations (A_{13}), the number of Internet broadband access ports (A_{14}), the capacity of mobile phone exchanges (A_{15}), the total length of cable broadcasting and television transmission trunk networks (A_{16}), the number of Internet domain names (A_{21}), the number of Internet web pages (A_{21}), and IPv4 Number of addresses (A_{23}), mobile Internet access traffic (A_{24}).

The digital environment (B) serves as the carrier for the development of the digital economy and is composed of ten indicators, namely the digital development environment (B_1) and the digital financial environment (B_2). This includes the telephone penetration rate (B_{11}), the number of mobile phone users (B_{12}), the number of digital TV users (B_{13}), the computer penetration rate (B_{14}), the number of mobile Internet users (B_{15}), the number of broadband access users (B_{16}), the electronic payment index (B_{21}), the digital finance coverage breadth index (B_{22}), and the digital finance usage depth index (B_{23}) The Digital Index of Inclusive Finance (B_{24}).

Digital application (C) is one of the important manifestations of the current development status of the digital economy, consisting of 10 indicators including digital industrialization (C_1) and industrial digitalization (C_2). Including software business revenue (C_{11}), software product revenue (C_{12}), information technology service revenue (C_{13}), telecommunications business revenue (C_{14}), the number of enterprises in the electronic equipment manufacturing industry (C_{15}), the number of enterprises with e-commerce activities (C_{21}), the number of websites owned by each enterprise (C_{22}), and the number of computers used per unit population of an enterprise (C_{23}). Enterprise e-commerce sales (C_{24}), total online retail sales (C_{25}).

Digital innovation (D) provides technical support for the development of the digital economy and is composed of 10 indicators including digital innovation input (D_1) and digital innovation output (D_2). Including the full-time equivalent of R&D personnel (D_{11}), expenditure on basic research (D_{12}), expenditure on applied research (D_{13}), expenditure on experimental development (D_{14}), the proportion of

R&D expenditure to GDP (D_{15}), the number of new product development projects (D_{21}), the number of enterprise units with R&D activities (D_{22}), and the number of patent applications (D) $_{23}$) The number of invention patent applications (D_{24}) and the transaction volume of the technology market (D_{25}).

As can be seen from table 1, among the first-level indicators, digital innovation has the largest weight, at 0.394, followed by digital application, with a weight of 0.304. The weights of digital foundation and digital environment are 0.209 and 0.093, respectively, which indicate that digital innovation and digital application have a key impact on the development of the digital economy. Investing in these two aspects will help promote the rapid increase in the level of digital economy development. Meanwhile, the digital foundation provides infrastructure support for the digital economy and plays an important role in the development of the digital economy in each province. Observe the weights of secondary indicators. The weights of the number of invention patent applications, the number of patent applications, the number of Internet web pages, the number of enterprise units with R&D activities, and the number of enterprise units in the electronic equipment manufacturing industry are 0.071, 0.066, 0.054, 0.052, and 0.049, respectively, and rank in the top five. This indicates that these indicators occupy a core position in the index system of digital economy development index. The number of invention patent applications and patent applications directly reflect a region's technological innovation capability, while the number of Internet web pages represents the wide application of information technology and the digitization process. The number of business units with R&D activities and the number of business units in the electronic equipment manufacturing industry highlight the popularity of R&D activities and the vibrancy of core industries in the digital economy. In addition, software business revenue, information technology service revenue, software product revenue, technology market turnover, and total online retail sales also have an important impact on the evaluation of the development level of the digital economy. Overall, these indicators are key drivers of the development of the digital economy and play a crucial role in its healthy and sustainable growth.

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

First-level indicators	Secondary indicators	Third-level indicators	Indicator attribute	Indicator weight
A (0.209)	A_1 (0.065)	A_{11}	Positive	0.013
		A_{12}	Positive	0.010
		A_{13}	Positive	0.011
		A_{14}	Positive	0.011
		A_{15}	Positive	0.009
		A_{16}	Positive	0.011
	A_2 (0.144)	A_{21}	Positive	0.027
		A_{22}	Positive	0.054
		A_{23}	Positive	0.034
		A_{24}	Positive	0.029
B (0.093)	B_1 (0.066)	B_{11}	Positive	0.009
		B_{12}	Positive	0.012
		B_{13}	Positive	0.012
		B_{14}	Positive	0.008
		B_{15}	Positive	0.012
		B_{16}	Positive	0.013
	B_2 (0.027)	B_{21}	Positive	0.006
		B_{22}	Positive	0.007
		B_{23}	Positive	0.007
		B_{24}	Positive	0.007
C (0.304)	C_1 (0.192)	C_{11}	Positive	0.043
		C_{12}	Positive	0.041
		C_{13}	Positive	0.043
		C_{14}	Positive	0.016
		C_{15}	Positive	0.049
	C_2 (0.112)	C_{21}	Positive	0.024
		C_{22}	Positive	0.005
		C_{23}	Positive	0.011
		C_{24}	Positive	0.032
		C_{25}	Positive	0.040
D (0.394)	D_1 (0.127)	D_{11}	Positive	0.025

		D_{12}	Positive	0.032
		D_{13}	Positive	0.029
		D_{14}	Positive	0.028
		D_{15}	Positive	0.013
	D_2 (0.267)	D_{21}	Positive	0.037
		D_{22}	Positive	0.052
		D_{23}	Positive	0.066
		D_{24}	Positive	0.071
		D_{25}	Positive	0.041

(2) Data sources and explanations

In order to accurately assess the development of China's digital economy, the Chinese government began to emphasize the development of digital economy in 2015 as the starting point of the study, and the time period of the study is 2015-2024. Restricted by the availability of data, the study object is the 30 provincial-level administrative regions in China, excluding Hong Kong, Macao, Taiwan and Tibet. The data of the relevant secondary indicators for evaluating the digital financial environment come from Peking University's Inclusive Finance Index, while the data of the remaining secondary indicators come from China Statistical Yearbook, China Tertiary Industry Statistical Yearbook, China Information Yearbook, and statistical yearbooks of each province, which are collected and organized with the help of CEIC Data Network, and the missing values are reasonably filled in.

(3) Analysis of digital economy development level index

Based on the digital economy development index system using the entropy value method, the digital economy development level from 2015 to 2024 is measured as shown in Table 2.

As a whole, the average value of China's digital economy development level index grows from 0.0981 in 2015 to 0.1840 in 2024, indicating that China's digital economy development level has been greatly improved from the whole. And the index of the level of digital economy development of each province has increased, indicating that the level of digital economy development of each province in China has also been significantly improved. In terms of the ranking of development level, the top five are Guangdong, Zhejiang, Jiangsu, Beijing and Shandong, all eastern provinces, and the index of the development level of digital economy in 2024 reaches 0.7092, 0.4846, 0.4339, 0.3612 and 0.3254 respectively, which is much higher than that of the bottom five, namely, Gansu (0.0658), Xinjiang (0.0371), Hainan (0.0641), Qingdao (0.0641), and Hainan (0.0641). 0.0641), Qinghai (0.0352) and Ningxia (0.0438). And in the bottom five provinces, containing only Hainan Province, an eastern province, indicating that China's digital economy development there are significant regional differences, and roughly the distribution of the "east high west low" trend. From the development gap, China's digital economy development average value of the highest of Guangdong and the lowest of Ningxia gap is large, in 2024, Guangdong's digital economy development index (0.7092) is still 16 times more than Ningxia (0.0438), there is still a large absolute difference. It is clear that China's balanced development of digital economy has a long way to go.

Table 2. The development level of the digital economy in 2015-2024.

Province	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024	Mean
Guangdong	0.2857	0.3277	0.3555	0.3488	0.4164	0.5146	0.6019	0.7193	0.8246	0.7092	0.5104
Zhejiang	0.2102	0.2242	0.2481	0.2729	0.2928	0.3366	0.4041	0.4775	0.5664	0.4846	0.3517
Jiangsu	0.2235	0.2719	0.2473	0.2921	0.3024	0.3521	0.3811	0.4558	0.5067	0.4339	0.3467
Beijing	0.1948	0.2099	0.2092	0.2267	0.2309	0.2719	0.2893	0.3165	0.3623	0.3612	0.2673
Shandong	0.1795	0.1854	0.1958	0.2215	0.2362	0.2826	0.3059	0.3121	0.3749	0.3254	0.2619
Shanghai	0.1401	0.1739	0.2143	0.2152	0.2212	0.2296	0.2673	0.2826	0.3052	0.3199	0.2369
Sichuan	0.1034	0.1252	0.1157	0.1204	0.1206	0.1475	0.1847	0.2314	0.2666	0.2225	0.1638
Fujian	0.1086	0.1169	0.1027	0.1165	0.1428	0.1403	0.1687	0.2057	0.2421	0.1723	0.1517
Henan	0.0945	0.0991	0.1163	0.1316	0.1316	0.1502	0.1793	0.2239	0.2472	0.1784	0.1552
Hebei	0.1069	0.1019	0.1051	0.0987	0.1096	0.1341	0.1528	0.1831	0.2413	0.1711	0.1405
Hubei	0.0869	0.0902	0.0765	0.1167	0.1334	0.1466	0.1585	0.1952	0.1993	0.1574	0.1361
Anhui	0.0712	0.0811	0.0815	0.1014	0.1175	0.1282	0.1753	0.1789	0.2233	0.1805	0.1339
Hunan	0.0829	0.1084	0.1177	0.0814	0.1126	0.1245	0.1479	0.1659	0.1921	0.1692	0.1303
Liaoning	0.0815	0.1061	0.1392	0.1181	0.1038	0.1271	0.1397	0.1373	0.1701	0.1275	0.1250
Shaanxi	0.0599	0.0612	0.0791	0.0933	0.0912	0.1021	0.1312	0.1565	0.1591	0.1235	0.1057
Chongqing	0.0515	0.0719	0.0923	0.1049	0.0751	0.1029	0.1109	0.1209	0.1741	0.1221	0.1027

Tianjin	0.0817	0.0775	0.0961	0.1012	0.0963	0.0831	0.1144	0.1235	0.1531	0.0977	0.1025
Yunnan	0.0681	0.0731	0.0836	0.0954	0.0737	0.0987	0.1233	0.1285	0.1528	0.0901	0.0987
Heilongjiang	0.0688	0.0839	0.0742	0.0853	0.0751	0.0911	0.0971	0.1277	0.1322	0.0832	0.0919
Guangxi	0.0724	0.0598	0.0707	0.0506	0.0624	0.0795	0.0983	0.1269	0.1765	0.0922	0.0889
Jiangxi	0.0443	0.0541	0.0502	0.0588	0.0637	0.0655	0.1104	0.1408	0.1723	0.1046	0.0865
Shanxi	0.0535	0.0626	0.0631	0.0643	0.0681	0.0588	0.0913	0.1203	0.1341	0.0934	0.0810
Guizhou	0.0414	0.0639	0.0613	0.0611	0.0564	0.0591	0.1174	0.1411	0.1695	0.0909	0.0862
Inner Mongolia	0.0539	0.0741	0.0448	0.0619	0.0662	0.0813	0.0911	0.1118	0.1147	0.1022	0.0802
Jilin	0.0534	0.0653	0.0735	0.0659	0.0779	0.0626	0.0689	0.1142	0.0983	0.0838	0.0764
Gansu	0.0597	0.0371	0.0414	0.0644	0.0666	0.0772	0.0723	0.1137	0.1347	0.0658	0.0733
Xinjiang	0.0622	0.0488	0.0626	0.0712	0.0578	0.0651	0.0911	0.0875	0.1257	0.0371	0.0709
Hainan	0.0339	0.0481	0.0466	0.0442	0.0181	0.0494	0.0741	0.0991	0.0939	0.0641	0.0572
Qinghai	0.0312	0.0335	0.0419	0.0479	0.0403	0.0431	0.0572	0.1095	0.1184	0.0352	0.0558
Ningxia	0.0407	0.0416	0.0355	0.0329	0.0375	0.0233	0.0646	0.1134	0.0892	0.0438	0.0523
Mean	0.0981	0.1095	0.1152	0.1228	0.1274	0.1457	0.1746	0.2074	0.2384	0.1840	0.1523

2.2.2. Analysis of the evolutionary dynamics of digital economic development

This paper invokes the method of adaptive kernel density estimation to reflect the spatial distribution non-equilibrium problem of the digital economy development level, so as to reveal the dynamic evolution process of the absolute difference of the digital economy development level at the national level and the four major regions. Where the vertical coordinate represents the Kernel density value and the horizontal coordinate represents the digital economy development index.

(1) Kernel density estimation of digital economy development level at the national level

The contour plot of the Kernel density estimation of the index of the level of digital economic development at the national level is shown in Figure 1. It can be seen that, firstly, the contour values of the kernel density estimation graph of the level of digital economic development become smaller, the contour lines become sparse, and there is a serious right trailing phenomenon, which indicates that there is an obvious gap in the level of China's digital economic development. Second, from the position of contour lines, the whole moves to the right, indicating that China's digital economy development level has improved in the study interval. Third, from the number of main peaks, the characteristic of "multiple peaks" is gradually weakening, indicating that the multipolarization phenomenon of China's digital economy has eased. Overall, the development level of China's digital economy has improved, but there are still obvious regional differences.

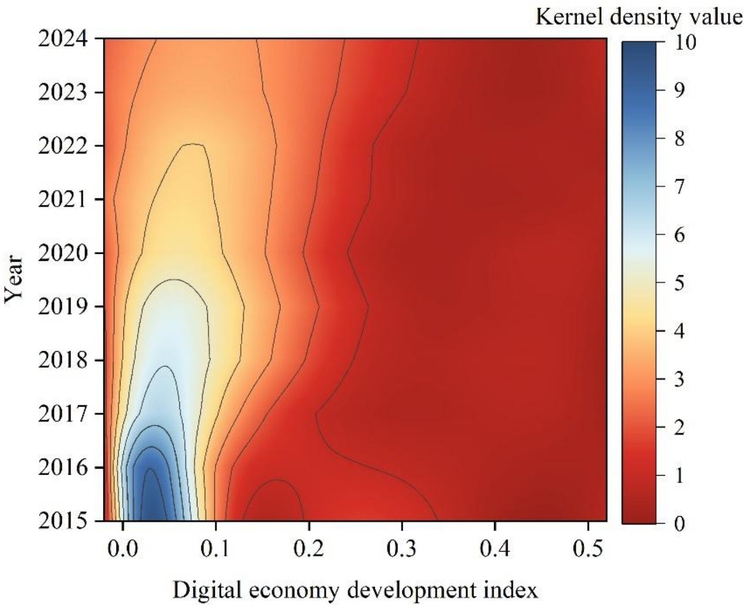


Figure 1. Contour map of nuclear density estimation at the national level.

(2) Kernel density estimation of the development level of digital economy in the four major regions

The contour map of the kernel density estimation of the level of digital economic development in the four major regions is shown in Figure 2, in which (a) to (d) denote the eastern region, central region, western region, and northeastern region, respectively.

1) Kernel density estimation in the eastern region

The contour of digital economy kernel density in the eastern region varies greatly. First, the kernel density estimation map of digital economic development level has become smaller in kernel density value, denser in contour lines, and the right trailing phenomenon is not obvious, which indicates that the gap in the level of digital economic development in eastern China has been narrowed. Second, from the position of contour lines, the whole obviously moves to the right, indicating that the level of digital economy development in eastern China has improved in the study interval. Third, in terms of the number of main peaks, the characteristic of "multiple peaks" has gradually changed to the characteristic of "double peaks", indicating that the multi-polarization phenomenon of digital economy development in eastern China has been alleviated. Overall, the level of digital economy development in Eastern China has improved, but there is still an obvious development gap among provinces.

2) Estimation of kernel density in the central region

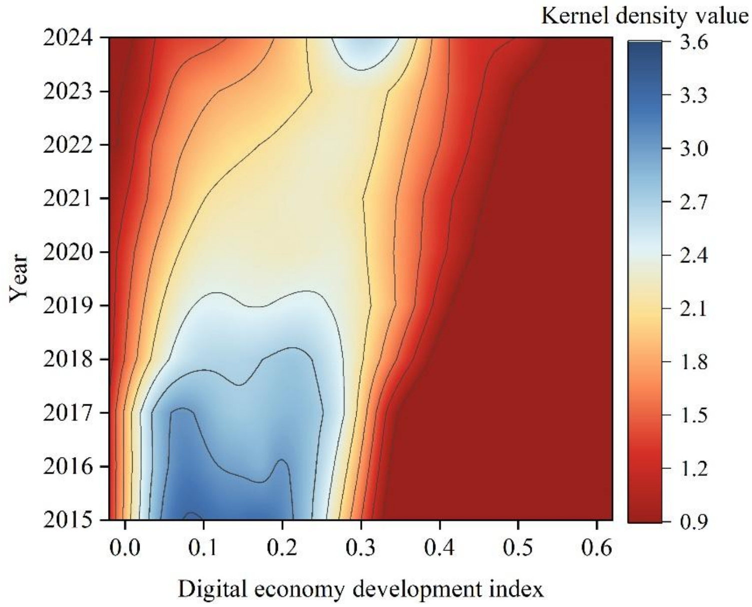
The kernel density curve in the central region is more complicated. First, the kernel density estimation map of digital economic development level kernel density value becomes smaller, and the contour line becomes slightly thinner, indicating that the difference in the level of digital economic development in the central region has not changed much, but it has expanded in 2024 compared with 2015. Second, from the position of the curve, the whole is obviously shifted to the right, indicating that the level of digital economy development in central China has increased in the study interval. Third, from the number of main peaks, the central region is characterized by "multiple peaks", and the right trailing phenomenon is obvious, indicating that there is a multi-polarization phenomenon in the level of digital economy development in the central region.

3) Estimation of Kernel Density in Western Region

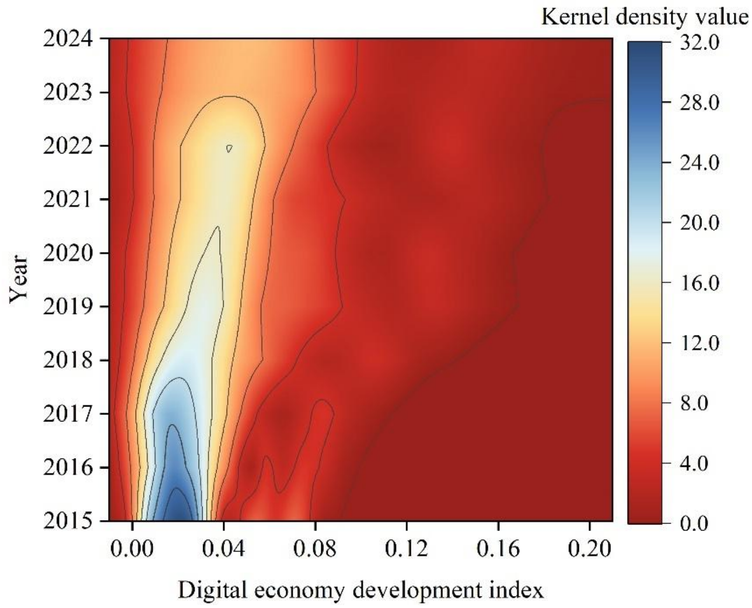
Kernel density curve in the western region is characterized by more obvious changes. First, the kernel density value of the kernel density estimation map of the level of digital economic development becomes smaller, and the contour lines become sparse, but there is no obvious right trailing phenomenon, indicating that the gap in the level of digital economic development in western China has increased. Secondly, from the position of the curve, the whole is obviously shifted to the right, indicating that the level of digital economy development in western China has increased within the study interval. Third, from the number of main peaks, the "double peaks" characteristic of the western region has weakened, indicating that the phenomenon of multi-polarization of the development of digital economy in the western region has been alleviated.

4) Estimation of kernel density in the northeast region

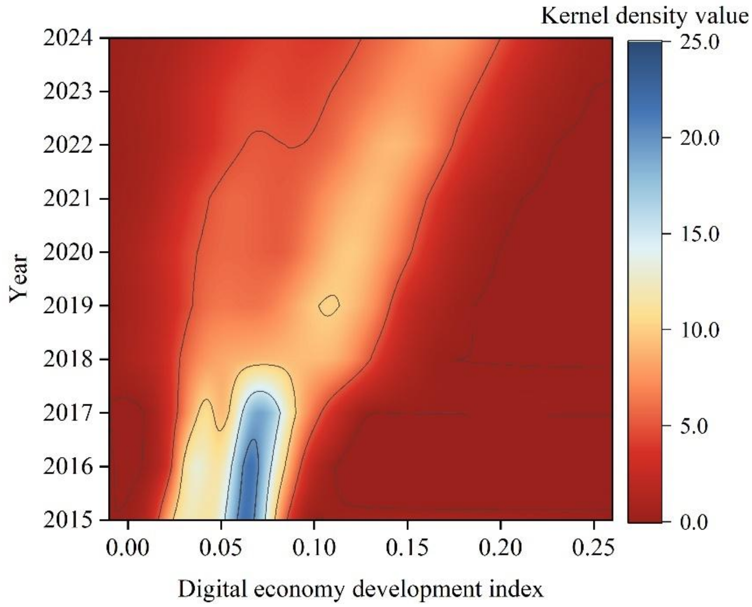
Northeast region's kernel density curve characteristics change more regularly. First, the kernel density value of the kernel density estimation map of the level of digital economic development has become smaller, and the contour lines have become sparse, indicating that the gap in the level of digital economic development in the northeast region has increased. Second, from the position of the curve, the whole is obviously shifted to the right, indicating that the level of digital economy development in Northeast China has increased in the study interval. Third, in terms of the number of main peaks, the northeast region shows a "double peak" characteristic of "one main peak and one side peak", but the distance between the double peaks has expanded, and the main peaks have become slower, which indicates that the development of the digital economy in the northeast region has a phenomenon of polarization, and the absolute difference has been enlarged.



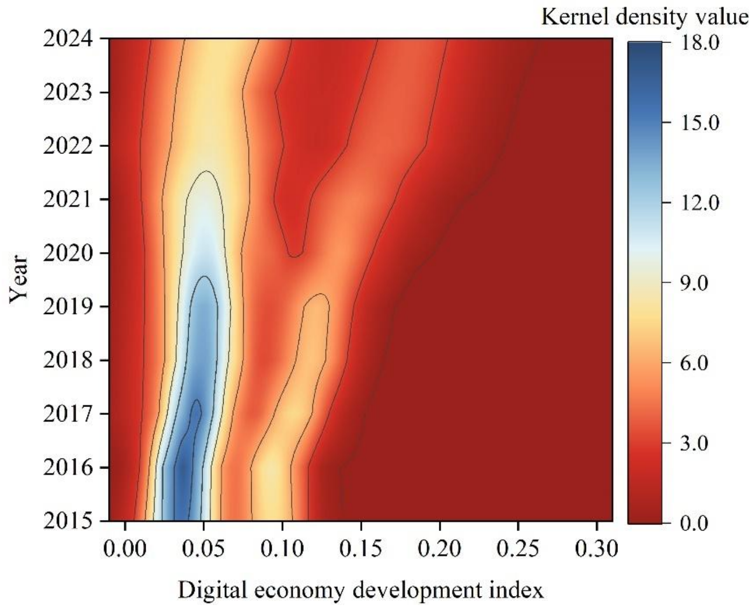
(a) The eastern region



(b) The central region



(c) The western region



(d) The northeast region

Figure 2. Contour map of nuclear density estimation in four major regions.

2.3. Measuring the efficiency of urban-rural integration and analyzing the evolution of dynamics

2.3.1. Measuring the efficiency of urban-rural integration

Urban-rural integrated development is a comprehensive concept, and most of the current research focuses on the construction of complex systems of economy, culture and social life. In this study, the connotation of urban-rural integrated development is explored from the perspectives of three elements: people (X), land (Y) and capital (Z), and the positive and negative aspects of the indicators and the input and output characteristics of the indicators are determined during the process of selecting the indicators. The data for this study are for the whole country and 30 provinces (except for Hong Kong, Macao and Taiwan), and are obtained from the provincial statistical yearbooks and the compendium of township administrative divisions of the People's Republic of China in the corresponding years. The proposed comprehensive evaluation index system of urban-rural integration development efficiency is shown in

Table 3, which consists of nine second-level indicators: economic level (X_1), social life (X_2), urbanization level (Y_1), technological progress (Y_2), arable land level (Y_3), transportation level (Y_4), investment and production (Z_1), agricultural support (Z_2), and investment and production discrepancy (Z_3), and is further subdivided into 14 Tertiary indicators: GDP per capita (X_{11}), the proportion of non-agricultural output (X_{12}), the level of public services (X_{21}), the level of social security (X_{22}), the urbanization rate (Y_{11}), the level of agricultural mechanization (Y_{21}), the percentage of arable land area (Y_{31}), the level of financial expenditures on transportation (Y_{41}), the status of railroads and highways (Y_{42}), and the level of investment in fixed assets (Z_{11}), Fixed Asset Investment Support for Agriculture (Z_{21}), Fiscal Support for Agriculture (Z_{22}), Fixed Asset Investment Difference (Z_{31}), Price Index Level Difference (Z_{32}). The weights of the indicators are calculated by the entropy value method.

It can be seen that the integration of capital is the most important element in promoting the further development of urban-rural integration, with a weight of 0.747, while the integration of people is slightly higher than the integration of land, with a weight of 0.141 and 0.112, respectively. Further, the level of investment in fixed assets (0.204) and the difference in investment in fixed assets between urban and rural areas (0.169) are the most important factors affecting the development of urban-rural integration.

Table 3. Evaluation index system for the efficiency of integrated urban-rural development.

Target layer	Project layer	Indicator layer	Indicator attribute	Indicator characteristics	Indicator weight
X (0.141)	X_1 (0.068)	X_{11}	Positive	Output	0.036
		X_{12}	Positive	Output	0.032
	X_2 (0.073)	X_{21}	Positive	Input	0.046
		X_{22}	Positive	Input	0.027
Y (0.112)	Y_1 (0.038)	Y_{11}	Positive	Output	0.038
	Y_2 (0.023)	Y_{21}	Positive	Output	0.023
	Y_3 (0.021)	Y_{31}	Negative	Output	0.021
	Y_4 (0.030)	Y_{41}	Positive	Input	0.017
		Y_{42}	Positive	Output	0.013
Z (0.747)	Z_1 (0.204)	Z_{11}	Positive	Input	0.204
	Z_2 (0.238)	Z_{21}	Positive	Input	0.102
		Z_{22}	Positive	Input	0.136
	Z_3 (0.305)	Z_{31}	Positive	Input	0.169
		Z_{32}	Positive	Output	0.136

2.3.2. Analysis of the evolutionary dynamics of urban-rural integration efficiency

(1) Evolutionary dynamics at the regional level

The trend of the urban-rural integration index from 2015 to 2024 is shown in Figure 3. Looking at the country as a whole, China's urban-rural integration index as a whole shows an upward trend in fluctuation during 2015-2024, rising from 0.395 in 2015 to 0.408 in 2024, an increase of 3.29%. By region, the urban-rural integration development in the eastern region as a whole shows a slow rise, from 0.479 in 2015 to 0.486 in 2024, an increase of 1.46%, and the urban-rural integration index shows a slight fluctuation trend as a whole during the period of 2015-2021, and the fluctuation amplitude increases significantly during the period of 2022-2024. The urban-rural integration index of the central region fluctuates less throughout the sample years, roughly fluctuating slightly around the 0.40 fluctuation axis, with an overall upward trend during the sample years from 0.396 in 2015 to 0.401 in 2024, an increase of 1.26%. The growth trend of the urban-rural integration index in the western region is more obvious than that in the eastern and central regions, rising from 0.307 in 2015 to 0.325 in 2024, an increase of 5.86%. Overall, the level of urban-rural integration in China gradually decreases from the east to the center and the west, with an overall upward trend.

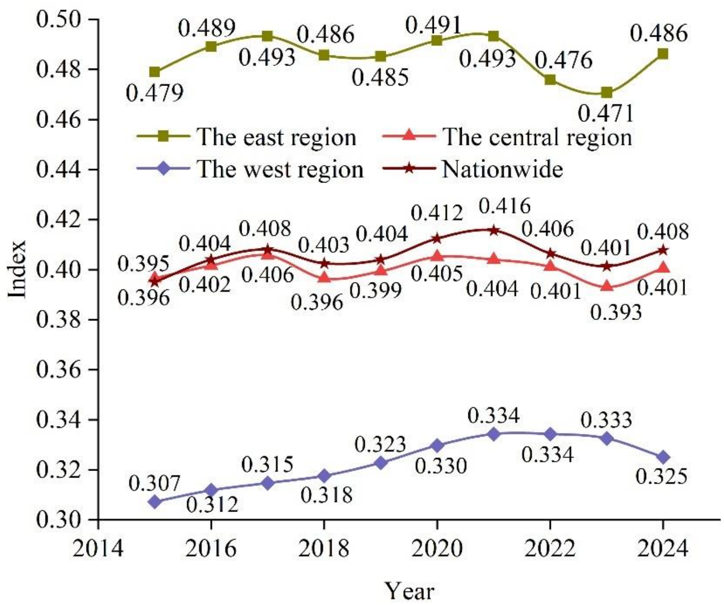


Figure 3. Trend of the urban-rural integration development index from 2015 to 2024.

(2) Evolutionary dynamics at the provincial level

In order to further characterize the evolution of the urban-rural integration index at the provincial level in China, this study summarizes the mean value of the total index of urban-rural integration level and the mean value of each subindex as shown in Table 4. From the mean value of the total urban-rural integration index, the top five provinces in descending order are Shanghai, Zhejiang, Jiangsu, Beijing, and Guangdong, and all of the above provinces belong to the eastern region. The bottom five provinces, in descending order, are Gansu, Ningxia, Xinjiang, Qinghai and Yunnan, all of which belong to the western region. From the mean value of each index, in terms of integration of people, the top five provinces in descending order are Shanghai, Beijing, Tianjin, Zhejiang and Guangdong, all of which are located in the eastern region, while the bottom five provinces in descending order are Xinjiang, Sichuan, Ningxia, Gansu and Yunnan, all of which are located in the western region. In terms of geographical integration, the top five provinces in descending order are Shanghai, Henan, Jiangsu, Shandong, and Beijing, with the exception of Henan province, which belongs to the central region, and the rest of the provinces belong to the eastern region, and the bottom five provinces in descending order are Xinjiang, Qinghai, Heilongjiang, Gansu, and Hainan, with the exception of Hainan and Heilongjiang, and the rest of the three provinces belong to the western region. In terms of capital integration, the top five provinces in order from high to low are Zhejiang, Jiangsu, Hebei, Fujian and Shandong, with all of the above provinces belonging to the eastern region, and the bottom five provinces in order from low to high are Gansu, Ningxia, Xinjiang, Guizhou and Qinghai, with all of the above provinces belonging to the western region. Overall, the level of urban-rural integration is highest in the eastern region, followed by the central region, and lowest in the western region.

Table 4. The average urban-rural integration index of 30 sample provinces from 2015 to 2024.

	Province	Urban-rural integration	Human integration	The integration of the earth	The integration of capital
The east region	Beijing	0.5094	0.2094	0.1032	0.1968
	Tianjin	0.4682	0.1271	0.0918	0.2493
	Hebei	0.4633	0.0698	0.0906	0.3029
	Liaoning	0.4466	0.0912	0.0829	0.2725
	Shanghai	0.5605	0.2265	0.1743	0.1997
	Jiangsu	0.5162	0.0973	0.1137	0.3052
	Zhejiang	0.5209	0.1177	0.0821	0.3211
	Fujian	0.4294	0.0751	0.0554	0.2989
	Shandong	0.4783	0.0756	0.1089	0.2938
	Guangdong	0.4828	0.0996	0.0954	0.2878
	Hainan	0.3541	0.0687	0.0481	0.2373
	Mean	0.4763	0.1162	0.0942	0.2659

The central region	Shanxi	0.3871	0.0754	0.0673	0.2444
	Jilin	0.3559	0.0649	0.0513	0.2397
	Heilongjiang	0.3710	0.0626	0.0452	0.2632
	Anhui	0.4104	0.0653	0.1012	0.2439
	Jiangxi	0.4086	0.0837	0.0680	0.2569
	Henan	0.4361	0.0659	0.1172	0.2530
	Hubei	0.4144	0.0686	0.0864	0.2594
	Hunan	0.4073	0.0696	0.0916	0.2461
	Mean	0.3964	0.0670	0.0785	0.2508
The west region	Inner Mongolia	0.3572	0.0581	0.0566	0.2425
	Guangxi	0.3721	0.0621	0.0872	0.2228
	Chongqing	0.3594	0.0640	0.0957	0.1997
	Sichuan	0.3771	0.0444	0.0740	0.2587
	Guizhou	0.3283	0.0592	0.0880	0.1811
	Yunnan	0.3112	0.0508	0.0729	0.1875
	Shaanxi	0.3437	0.0669	0.0667	0.2101
	Gansu	0.2021	0.0500	0.0468	0.1053
	Qinghai	0.2814	0.0525	0.0446	0.1843
	Ningxia	0.2482	0.0492	0.0548	0.1442
	Xinjiang	0.2641	0.0399	0.0434	0.1808
	Mean	0.3132	0.0543	0.0664	0.1925

(3) Regional differences and sources

In order to further reveal the sources of the formation of differences in the spatial and temporal evolution of urban-rural integrated development, this paper adopts the Terrell index to decompose the evaluation index of the level of urban-rural integrated development and portray intra-regional differences and inter-regional differences, and the results of the decomposition of the Terrell index are shown in Table 5.

It can be seen that based on the perspective of the three major regions, the source of formation of urban-rural integration and development differences is mainly due to inter-group differences. Among them, the average contribution rate of intra-group differences is 30.5%, and the maximum and minimum contribution rates are 37.8% and 24.1% respectively. While the average contribution rate of between-group differences was 70.0%, with maximum and minimum contribution rates of 76.6% and 63.6%, respectively.

Specifically for each subdimension, the source of formation of human integration differences was intragroup differences. Among them, the average contribution rates of within-group and between-group differences are 50.1% and 49.7%, respectively, with a small difference in contribution rates between the two differences. The source of formation of the integration differences of the land is the within-group differences. Among them, the average contribution rate of intra-group differences was 71.8%, and the maximum and minimum contribution rates were 76.5% and 68.3%, respectively. While the average contribution of intergroup differences is 28.2%, the maximum and minimum contribution is 32.7% and 23.5% respectively. The source of formation of integration differences in capital is intra-group differences. In this case, the average contribution of intra-group differences is 61.6%, which is much larger than the average contribution of inter-group differences which is 37.9%.

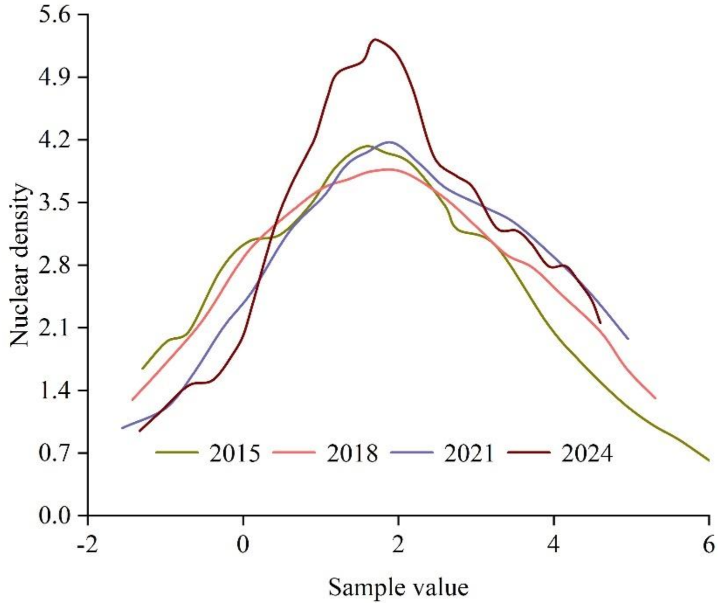
Table 5. Decomposition of the Thiel index for urban-rural integrated development.

	Overall differences		Human integration		The integration of the earth		The integration of capital	
Year	Within the group	Between groups	Within the group	Between groups	Within the group	Between groups	Within the group	Between groups
2015	0.293	0.703	0.551	0.447	0.699	0.295	0.466	0.530
2016	0.253	0.730	0.502	0.474	0.683	0.309	0.483	0.492
2017	0.241	0.766	0.481	0.513	0.698	0.306	0.503	0.498
2018	0.266	0.734	0.524	0.470	0.717	0.286	0.479	0.534
2019	0.281	0.727	0.558	0.471	0.772	0.235	0.479	0.521
2020	0.329	0.685	0.479	0.530	0.731	0.265	0.611	0.380
2021	0.316	0.693	0.472	0.506	0.685	0.327	0.686	0.306

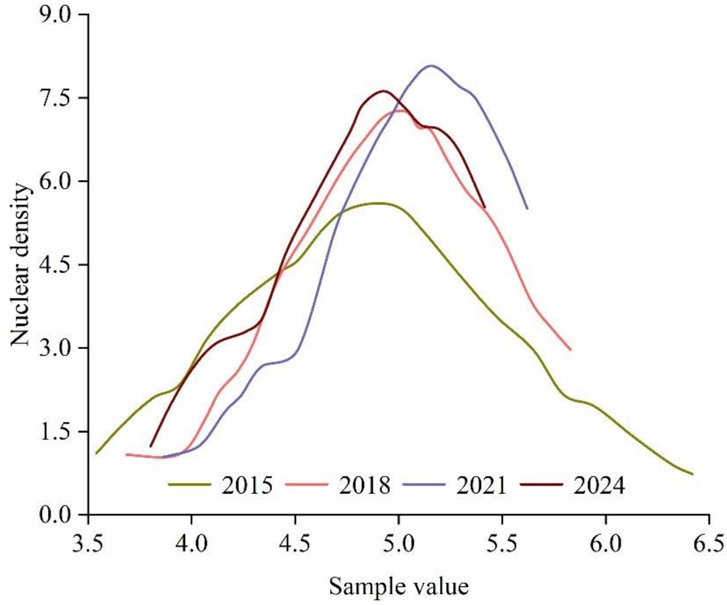
2022	0.366	0.638	0.453	0.544	0.765	0.249	0.741	0.263
2023	0.331	0.685	0.495	0.498	0.707	0.299	0.822	0.167
2024	0.378	0.636	0.495	0.519	0.718	0.253	0.890	0.095
Mean	0.305	0.700	0.501	0.497	0.718	0.282	0.616	0.379

In order to deeply analyze the development level of urban-rural integration development and the changing dynamics of regional differences during the sample years, this paper adopts the kernel density estimation method to portray the distribution of the comprehensive evaluation index of urban-rural integration development. The results of kernel density estimation are shown in Figure 4, where the horizontal coordinate is the level of urban-rural integration development and the vertical coordinate is the distribution density. Figures (a) to (d) represent the whole country, the east, the center, and the west, respectively.

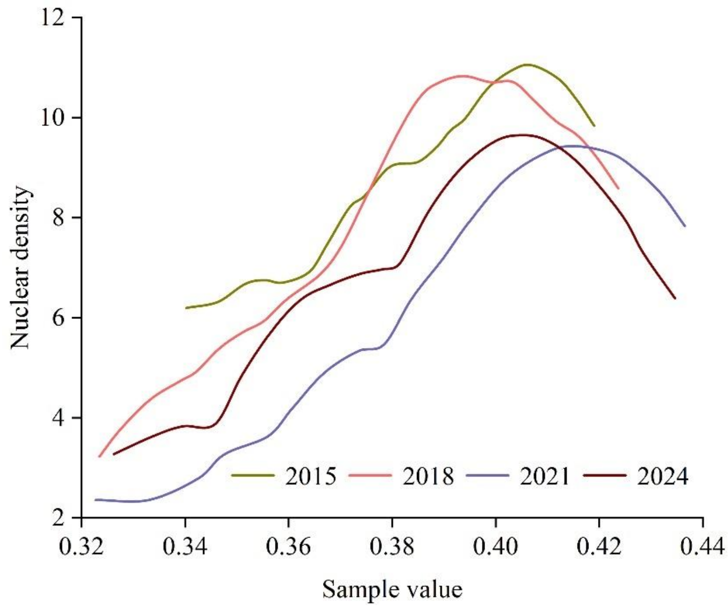
From the national level, the kernel density curve as a whole does not move significantly during the period 2015-2024, during which the height of the wave crest rises and the width of the wave crest shows a change from a "broad peak" to a "sharp peak", indicating that the differences in the level of urban-rural integration and development at the national level are gradually narrowing. This indicates that the difference in the level of urban-rural integration and development at the national level is gradually narrowing. For the eastern region, the kernel density curve shows a significant rightward shift during the sample year, which means that the level of urban-rural integration and development in the eastern region has risen significantly, while the height of the peak rises and the width of the peak decreases, which means that the level of urban-rural integration and development in the eastern region is on a narrowing trend. For the central region, the kernel density curve of the level of urban-rural integration and development has gone through the stage of "left shift-right shift-return" during the sample years and has a multi-peak distribution, during which the height of the wave peaks decreases and the width of the wave peaks increases, which means that the level of urban-rural integration and development in the central region is expanding and polarization phenomenon occurs. In addition, during the period of 2018-2024, there is a left trailing phenomenon, indicating that there are more provinces below the average level of the central region and the distribution is not balanced. The kernel density curve of urban-rural integration and development level in the western region is significantly shifted to the right, indicating that the urban-rural integration level in the western region as a whole is on the rise, and the height of the wave crest rises, and the width of the wave crest undergoes the evolutionary process of becoming wider and then narrowing, which indicates that the urban-rural integration level in the western region in general undergoes the process of expanding and then narrowing.



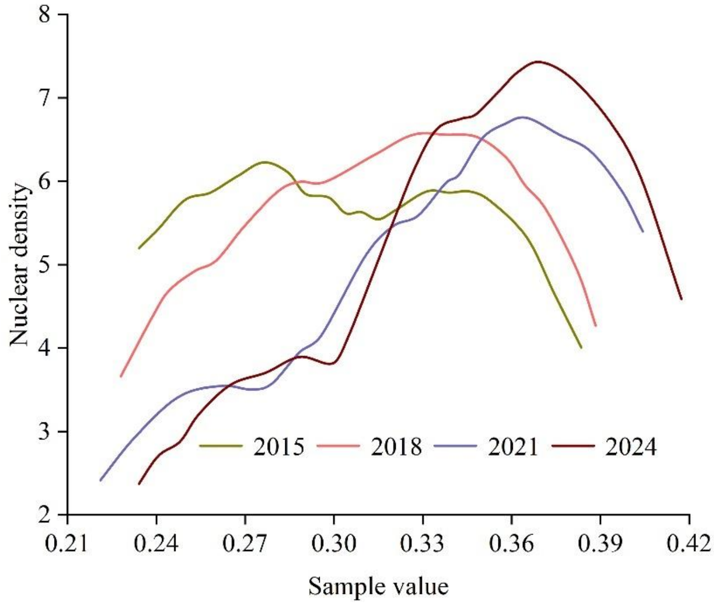
(a) Nationwide



(b) The eastern region



(c) The central region



(d) The western region

Figure 4. Spatio-temporal evolution trend of integrated urban-rural development.

3. Spatial econometric analysis of the impact of the digital economy on the efficiency of urban-rural integration

This chapter uses spatial econometric modeling to provide a deeper inquiry into the impact of the digital economy on the efficiency of urban-rural integration.

3.1. Theories related to spatial econometrics

3.1.1. Spatial autocorrelation test

Spatial autocorrelation test is used to determine whether the research object is suitable for the establishment of spatial measurement model, including global spatial autocorrelation test and local spatial autocorrelation test.

(1) Global spatial autocorrelation test

Global spatial autocorrelation test measures mainly include global Moran index, Gillray index and so on, among which global Moran index is the most commonly used one. The global Moran's I index is a comprehensive evaluation index used to measure the degree of overall spatial autocorrelation, reflecting the distribution characteristics of spatially neighboring regions. In this paper, the global Moran's index is calculated to reflect the average degree of agglomeration of digital economy development and urban-rural integration efficiency in 30 provinces. Taking digital economy development as an example, the calculation method of Moran's I index is shown in equation (10):

$$I = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\left(x_i - \bar{x}\right)\left(x_j - \bar{x}\right)}{S^2 \sum_{i=1}^{n}\sum_{i=1}^{n} w_{ij}} \tag{10}$$

where x_i and x_j denote the size of the digital economy of the i and j provinces, respectively, $\bar{x}$ denotes the average of the size of the digital economy of the 30 provinces, S^2 stands for the variance of the size of the digital economy, and w_{ij} is the spatial weight matrix. I lies between $(-1,1)$, and if Moran's I index is in the range of 0 to 1, it indicates the existence of global positive correlation. If the Moran's I index is in the range of -1 to 0, it indicates the presence of a global negative correlation. In addition, Moran's I index tends to be characterized by a random distribution as it approaches 0.

Hypothesis testing of the Moran's I index is also required. When n is large enough, Moran's I index approximately obeys a normal distribution, so we can test it with the Z-statistic, and Eq. (11) is the calculation of the Z-statistic:

$$Z = \frac{I - E(I)}{\sqrt{\mathrm{var}(I)}} \tag{11}$$

(2) Local spatial autocorrelation test

Local Moran's index is the decomposed form of global Moran's index. Local spatial autocorrelation analysis can describe the degree of similarity in the level of digital economic development between each province and its region and neighboring provinces, and the common indexes are mainly the local Moran's I index of each province, and the calculation method is shown in equation (12):

$$I = \frac{\left(x_i - \overline{x}\right)\sum_{j=1, j\neq i}^{n} w_{ij}\left(x_j - \overline{x}\right)}{S^2} \tag{12}$$

In local autocorrelation analysis, Moran scatter plots and Lisa agglomeration plots are generally used for analysis. In this paper, these two visualizations are also used to explore the spatial aggregation patterns of digital economy and urban-rural integration efficiency in neighboring provinces.

3.1.2. Spatial econometric models

Traditional linear spatial models include the spatial lag model (SAR), spatial error model (SEM) and spatial Durbin model (SDM) [40].

The general expression of the spatial panel model is shown in equation (13):

$$\begin{aligned} &Y = \rho WY + X\beta + WX\theta + \mu + \xi + u \\ &u = \lambda Wu + \varepsilon \\ &\varepsilon \sim N\left(0, \sigma^2 I\right) \end{aligned} \tag{13}$$

where X denotes the matrix of explanatory variables and Y denotes the vector of explanatory variables. μ and ξ denote spatial fixed effects and time fixed effects, respectively, and ε is the error term. W denotes the spatial weight matrix. WX, WY are the spatial lag terms of the explanatory and interpreted variables, respectively, and Wu denotes the existence of interaction effects between the error terms. ρ denotes the spatial autoregressive coefficient, which represents the degree of spatial interaction between the explanatory variables, β denotes the regression coefficient of the explanatory variables, θ denotes the spatial response strength of the explanatory variables, and λ denotes the coefficients of the spatial error terms of the explanatory variables.

Based on the general expression, it can be transformed into different spatial panel models by adding relevant restrictions.

When $\lambda = 0, \theta = 0$, the model can be transformed into a SAR model with the model expression:

$$\begin{aligned} &Y = \rho WY + X\beta + \mu + \xi + \varepsilon \\ &\varepsilon \sim N\left(0, \sigma^2 I\right) \end{aligned} \tag{14}$$

When $\rho = 0, \theta = 0$, the model can be transformed into an SEM model with the model expression:

$$\begin{aligned} &Y = X\beta + \mu + \xi + u \\ &u = \lambda Wu + \varepsilon \\ &\varepsilon \sim N\left(0, \sigma^2 I\right) \end{aligned} \tag{15}$$

When $\lambda = 0$, this can be transformed into an SDM model with the model expression:

$$\begin{aligned} &Y = \rho WY + X\beta + WX\theta + \mu + \xi + \varepsilon \\ &\varepsilon \sim N\left(0, \sigma^2 I\right) \end{aligned} \tag{16}$$

In the SDM model, the explanatory variables are simultaneously affected by the explanatory variables, the spatial lag terms of the explanatory variables, and the spatial lag terms of the explanatory variables. Due to the bias in the regression coefficients obtained by direct regression on the above model, the effect of the explanatory variables on the explained variables can be further processed using the partial differentiation method to decompose them into direct and indirect effects.

The diagonal element of $(I-\rho W)^{-1}\left(I-\beta_k+W\theta_k\right)$ denotes the direct effect, which refers to the degree of influence of the k th explanatory variable of a certain spatial unit on the explanatory variables of that spatial unit. The off-diagonal elements of $(I-\rho W)^{-1}\left(I-\beta_k+W\theta_k\right)$ denote the indirect effects, which represent the extent to which the k th explanatory variable of a spatial cell affects the explanatory variables in the other spatial cells, and the sum of the direct effects and indirect effects is is the total effect.

3.1.3. Semi-parametric spatial panel models

Considering that the explanatory variables and the explained variables may have a certain nonlinear relationship, a semiparametric spatial panel model can be built by adding a nonparametric part to the linear model.

The expression of the semiparametric panel spatial Durbin model is:

$$Y=\rho WY+X\beta+WX\theta+m(z)+\varepsilon \tag{17}$$

where Y denotes the vector of explanatory variables, X denotes the vector of explanatory variables, and z denotes the vector of explanatory variables for the nonparametric part. $m(Z)$ denotes the unknown parametric part, and W denotes the spatial weight matrix. β denotes the coefficients of the explanatory variables, θ denotes the coefficients of the spatial lagged terms of the explanatory variables, and ρ denotes the spatial autoregressive coefficients, which represent the magnitude of the influence of the neighboring regions on the region. The ε denotes the random error term and it is assumed that none of the explanatory variables are correlated with the random error term.

Regarding the estimation method of model (17), it is first assumed that β, θ, and ρ are known, and conditional mathematical expectations are obtained on both sides of the model for Z:

$$m(z)=(I-\rho W)E(Y\mid z)-E(X\mid z)\beta-E(WX\mid z)\theta \tag{18}$$

where Z, Y, and X denote the vector of explanatory variables in the nonparametric part, and the vector of explanatory and explanatory variables in the parametric part, respectively. Preliminary estimates of $m(z)$ are obtained by using nonparametric estimation methods to obtain estimates of $E(Y\mid z)$, $E(X\mid z)$, and $E(WX\mid z)$ for $\hat{E}(Y\mid z)$, $\hat{E}(X\mid z)$, and $\hat{E}(WX\mid z)$, respectively:

$$\hat{m}(z,\rho,\beta,\theta)=(I-\rho W)\hat{E}(Y\mid z)-\hat{E}(X\mid z)\beta-\hat{E}(WX\mid z)\theta \tag{19}$$

Substituting Eq. (19) into Eq. (17) and collating yields the following equation:

$$\begin{aligned} Y-\hat{E}(Y|z)=\rho W(Y-\hat{E}(Y\mid z)+(X-\hat{E}(X\mid z))\beta \\ +(WX-\hat{E}(WX|z))\theta \end{aligned} \tag{20}$$

The parameter estimation method is utilized to obtain estimates of the parameters ρ, β, θ for model (19) $\hat{\rho}$, $\hat{\beta}$, $\hat{\theta}$, and, finally, the final estimate of the nonparametric function $m(z)$ is obtained from equation (19) $\hat{m}(z)=\hat{m}(z,\rho,\beta,\theta)$.

3.1.4. Setting of the spatial weighting matrix

The spatial weight matrix mainly includes four kinds, which are spatial 0-1 weight matrix, inverse distance spatial weight matrix, spatial economic weight matrix and spatial economic distance nested weight matrix, among which the first two kinds reflect the relevant information of geographic location. The research content of this paper is based on the spatial influence problem of geographic location in 30 provinces, so this paper chooses the spatial 0-1 weight matrix for subsequent research.

The spatial weight matrix W can represent the spatial adjacency between different provinces. The spatial neighborhood weight matrix is a binary symmetric matrix with the following matrix form:

$$W=\begin{Bmatrix} w_{11} & \cdots & w_{1n} \\ \vdots & \vdots & \vdots \\ w_{n1} & \cdots & w_{nn} \end{Bmatrix} \tag{21}$$

where W is a n-order matrix representing the neighborhood of each province to each other, where $w_{ij}(i=1,\Lambda,n,j=1,\Lambda,n)$ denotes the neighborhood of the first i-province's adjacency to the j-province. The elements w_{ij} on the diagonal of the spatial adjacency weight matrix are all 0, and the metric of w_{ij} is based on different criteria.

There are three kinds of adjacency rules for spatial adjacency weight matrix, which are ROOK adjacency, Queen adjacency and Bishop adjacency. The difference between the three is that ROOK adjacency takes common edge as adjacency, Queen adjacency takes common edge or common point as adjacency, and Bishop adjacency takes common point as adjacency. In this paper, we use the ROOK adjacency rule, i.e., two provinces are judged to be adjoining if there is a common boundary of non-zero length between them, i.e., spatial interaction will occur. Namely:

$$w_{ij}=\begin{cases}1, & \text{Region } i \text{ and region } j \text{ are adjacent}\\ 0, & \text{Region } i \text{ and region } j \text{ are not adjacent and } i=j\end{cases} \tag{22}$$

In Equation (22), i,j denotes the i th and j th province, respectively, and $i,j\in[1,n],n$ is the total number of provinces studied. According to the ROOK adjacency rule, when two provinces have a common boundary then w_{ij} is denoted as 1, otherwise w_{ij} is denoted as 0.

3.2. Spatial econometric modeling

(1) Model construction

Since this paper mainly explores the impact of digital economy on the efficiency of urban-rural integration and its spatial spillover, the spatial econometric model is selected for empirical analysis. The specific spatial estimation model constructed is as follows:

$$\begin{aligned}EURI_{it}&=\delta\sum\nolimits_{j=1}^{n}w_{ij}EURI_{jt}+\alpha Dige_{it}+\gamma CONTR_{it}+\beta\sum\nolimits_{j=1}^{n}w_{ij}Dige_{jt}\\&+\xi\sum\nolimits_{j=1}^{n}w_{ij}CONTR_{jt}+u_i+v_t+\mu_{it}\end{aligned} \tag{23}$$

$$\mu_{it}=\lambda\sum\nolimits_{j=1}^{n}w_{ij}\mu_{jt}+\varepsilon_{it} \tag{24}$$

where $EURI$ is the efficiency of urban-rural integration, w_{ij} is the (i,j) element of the spatial weight matrix W, δ, α, γ, β, ξ, and λ are the parameters to be estimated, and u_i is the individual effect term, v_t is the time effect term, and μ_{it}, ε_{it} are the random error terms. $Dige$ is the digital economy index and CONTR is each control variable. For the selection of the spatial weight matrix, this paper selects the economic-geographical nested weight matrix for empirical testing.

(2) Variable Selection

1) Explained variable: efficiency of urban-rural integration ($EURI$).

2) Explanatory variable: digital economy ($Dige$).

3) Mediating variable:

The level of economic development (*PGDP*), expressed as per capita gross regional product.

Quality of employment (*Qua*), measured through the average wage of the city's on-the-job workers.

Social security level (*Enin*), measured through the number of urban workers participating in pension insurance.

(4) Control variables: in order to be able to explore the correlation between the digital economy and the efficiency of urban-rural integration more comprehensively, this paper sets the following six control variables.

Labor Mobility (*Lm*), measured by the proportion of the employed population in the three major industries to the annual average population.

Education investment (*Edu*), expressed as education expenditure in government fiscal expenditure.

Fiscal decentralization (*Finadp*), expressed as the ratio of fiscal budgeted revenue to fiscal budgeted expenditure.

Financial development level (*Finance*), expressed as the ratio of institutional deposit and loan balances to regional GDP.

Openness to the outside world (*Open*), expressed as the ratio of foreign direct investment to regional GDP.

Human capital (*InHum*), measured by the logarithm of the average number of years of schooling of students enrolled in prefecture-level cities.

(3) Data description

Based on the availability of city data, this paper selects the panel data of 270 cities from 2015-2024 as the research object, and the relevant data of cities are mainly from China Urban Statistical Yearbook, Peking University Digital Financial Inclusion Index, CNRDS China Research Data Service Platform, IRIEC database, CSMAR database, Wind database, and provincial statistical yearbooks.

3.3. Analysis of spatial effects

3.3.1. Spatial correlation tests

(1) Global autocorrelation test

In this paper, we first use Matlab2019 to carry out global Moran's test on the urban-rural integration efficiency and digital economy index of 30 provinces and municipalities in China from 2015 to 2024 according to the principles described in the previous section, and the global Moran's index is shown in Table 6. It can be seen that the Moran indices of both urban-rural integration efficiency and digital economy index in 2015-2024 are positive and significant at the 0.01 level, which indicates that both urban-rural integration efficiency and digital economy index have strong positive spatial autocorrelation, i.e., the provinces around the provinces with high (low) urban-rural integration efficiency are also higher (lower) in urban-rural integration efficiency, and the distribution of the level of digital economy development in the space is also similar . In addition, in terms of the change of Moran's index over time, the Moran's index of urban-rural integration efficiency for 2015-2024 fluctuates slightly around 0.506, indicating that the degree of spatial autocorrelation of China's urban-rural integration efficiency is relatively stable during this decade. On the other hand, the Moran Index of the Digital Economy Index shows a trend of increasing and then decreasing, indicating that the spatial correlation of China's digital economy development level did not remain stable after the increase, but rather declined, but is still at a high level overall.

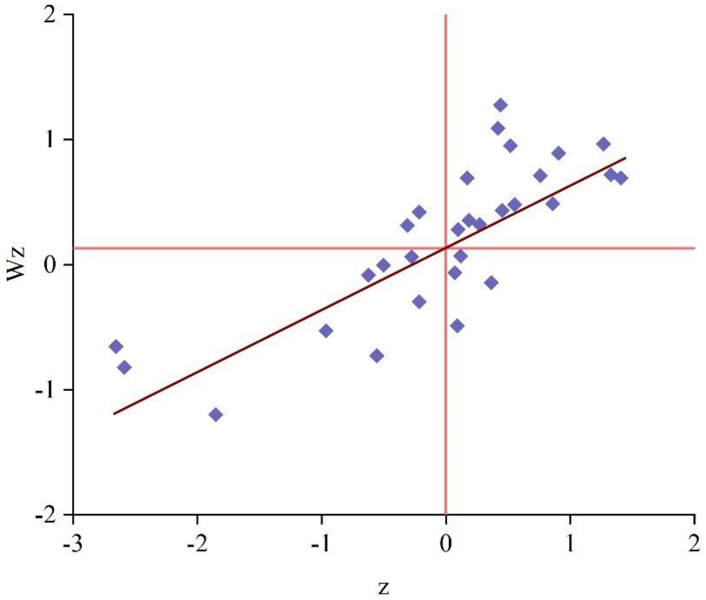
Table 6. Global Moran′s Ⅰ index.

	Efficiency of urban-rural integration			Digital economy index		
Year	Moran's I	z	p-value	Moran's I	z	p-value
2015	0.504	4.657	0.000	0.251	2.358	0.021
2016	0.506	4.674	0.000	0.275	2.573	0.012
2017	0.504	4.629	0.000	0.275	2.614	0.011
2018	0.506	4.673	0.000	0.283	2.647	0.009
2019	0.509	4.682	0.000	0.316	2.921	0.004
2020	0.506	4.671	0.000	0.311	2.835	0.005
2021	0.504	4.654	0.000	0.286	2.712	0.008
2022	0.504	4.662	0.000	0.284	2.673	0.009
2023	0.506	4.673	0.000	0.281	2.625	0.010
2024	0.508	4.685	0.000	0.257	2.459	0.015

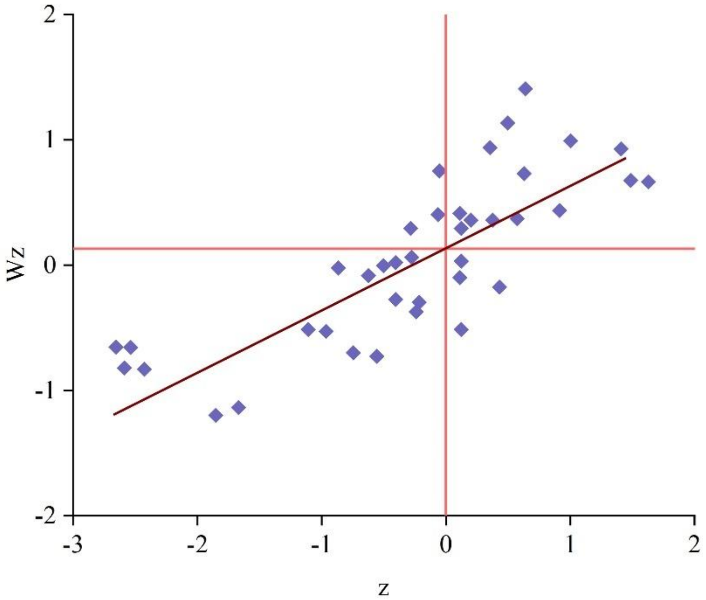
(2) Local autocorrelation test

This paper further analyzes the spatial agglomeration characteristics of Chinese provinces and municipalities by drawing Moran scatter plots of urban-rural integration efficiency and digital economy index in 2015 and 2024, and organizes the provinces included in each quadrant into a table based on the Moran scatter plots. The Moran scatter plots of urban-rural integration efficiency and digital economy index are shown in Figures 5 and 6, respectively, and the corresponding provinces in the four quadrants of the Moran scatter plots are shown in Tables 7 and 8, respectively. Analyzing the graphs, it can be seen that the vast majority of Chinese provinces are in the high-value-high-value quadrant and low-value-low-value quadrant in both the urban-rural integration efficiency and the digital economy index, and only a small number of provinces are in the low-value-high-value quadrant and high-value-low-value quadrant.

Combined with Figure 5 and Table 7, it can be seen that in 2015, urban-rural integration efficiency was located in the high-value-high-value quadrant in the largest number of provinces, with 15, accounting for 50% of the country. This is followed by provinces located in the low-value-low-value quadrant, with 9 provinces, accounting for 30% of the country. This indicates that most provinces with high values of urban-rural integration efficiency are surrounded by surrounding high values, and there is still much room for China's urban-rural integration efficiency to decline.The distribution of urban-rural integration efficiency by provinces and municipalities in the four quadrants of the Moran Scatterplot remains basically the same in 2024 compared with 2015, indicating that the changes in the urban-rural integration efficiency of all provinces and municipalities in China have been relatively stable, and that there is not a large gap between them. This indicates that the changes in the urban-rural integration efficiency of Chinese provinces and municipalities are relatively stable and have not widened the gap between them. Among them, only Chongqing has moved from the original high value-high value quadrant to the low value-high value quadrant, which indicates that the urban-rural integration efficiency of Chongqing has become smaller compared with the neighboring provinces over time, and is now surrounded by the neighboring provinces with relatively high urban-rural integration efficiencies, which shows that the urban-rural integration efficiency of Chongqing has been better improved.



(a) Efficiency of urban-rural integration in 2015



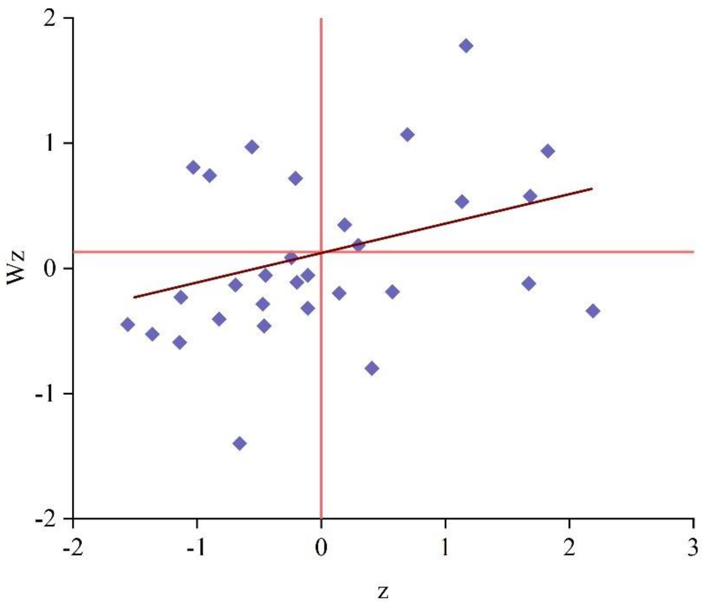
(b) Efficiency of urban-rural integration in 2024

Figure 5. Moran scatter plot of efficiency of urban-rural integration.

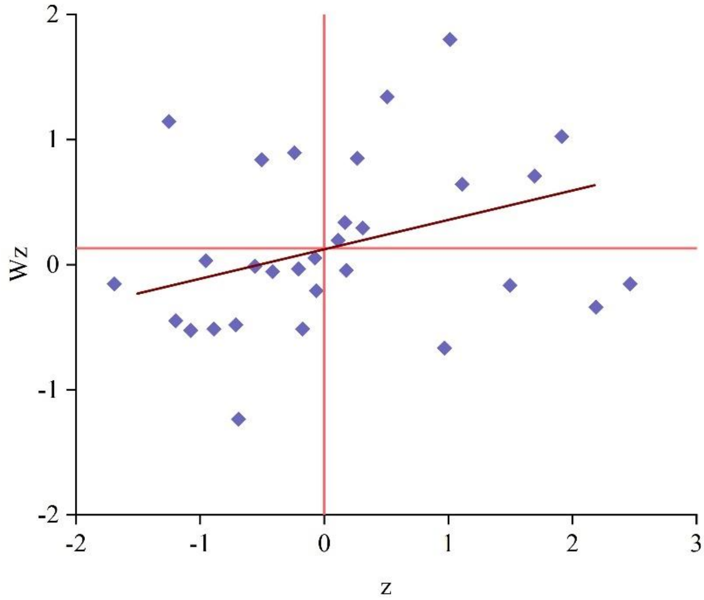
Table 7. The four quadrants of the efficiency of urban-rural integration.

Quadrant	In 2015	In 2024
High value - High value	Shanxi, Inner Mongolia, Henan, Hainan, Chongqing, Sichuan, Hunan, Ningxia, Xinjiang, Guangxi, Shaanxi, Qinghai, Yunnan, Guizhou, Gansu	Shanxi, Inner Mongolia, Henan, Hainan, Sichuan, Hunan, Ningxia, Xinjiang, Guangxi, Shaanxi, Qinghai, Yunnan, Guizhou, Gansu
Low value - High value	Guangdong, Hubei	Chongqing, Guangdong, Hubei
Low value - Low value	Shanghai, Tianjin, Beijing, Zhejiang, Jiangsu, Liaoning, Jilin, Heilongjiang, Fujian	Shanghai, Tianjin, Beijing, Zhejiang, Jiangsu, Liaoning, Jilin, Heilongjiang, Fujian
High value - Low value	Shandong, Hebei, Jiangxi, Anhui	Shandong, Hebei, Jiangxi, Anhui

From Figure 6 and Table 8: In both 2015 and 2024, the provinces with the digital economy level located in the low-value-low-value quadrant are the most numerous, with 14 provinces, accounting for 46.67% of the country, which indicates that nearly half of the provinces with low values of digital economy level are clustered with the surrounding low values, and the level of China's digital economy still has a large upside to be further improved. From the migration of provinces in the four quadrants of the Moran scatter plot, Anhui in the low-value-high-value quadrant and Hunan in the low-value-low-value quadrant migrated to the high-value-high-value quadrant, and Liaoning in the high-value-low-value quadrant migrated to the low-value-low-value quadrant. This suggests that both Anhui and Hunan have increased their digital economy levels relative to neighboring provinces, while Liaoning's lack of digital economy development is causing it to be overtaken by neighboring provinces.



(a) Digital economy in 2015



(b) Digital economy in 2024

Figure 6. Moran scatter plot of the digital economy.

Table 8. The provinces corresponding to the four quadrants for the digital economy.

Quadrant	In 2015	In 2024
High value - High value	Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Hebei, Henan	Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Hebei, Henan, Hunan, Anhui
Low value - High value	Tianjin, Hainan, Jiangxi, Anhui	Tianjin, Hainan, Jiangxi
Low value - Low value	Qinghai, Gansu, Ningxia, Xinjiang, Guizhou, Yunnan, Guangxi, Inner Mongolia, Heilongjiang, Jilin, Chongqing, Shaanxi, Hunan, Shanxi	Qinghai, Gansu, Ningxia, Xinjiang, Guizhou, Yunnan, Guangxi, Inner Mongolia, Heilongjiang, Jilin, Chongqing, Shaanxi, Shanxi, Liaoning
High value - Low value	Hubei, Liaoning, Beijing, Sichuan, Guangdong	Hubei, Beijing, Sichuan, Guangdong

3.3.2. Analysis of spatial effects regression results

On the basis of spatial correlation analysis, in order to select a suitable spatial econometric model to deeply analyze the spatial effect of digital economy affecting the efficiency of urban-rural integration. In this paper, Hausman, LM, Wald and LR tests were conducted on the regression results respectively. First, the Hausman test can determine whether the spatial econometric model uses random effects or fixed effects. Second, the LM test was used to further determine whether to select the spatial lag model (SLM) or the spatial error model (SEM), and the spatial Durbin model (SDM) was selected under the condition of determining the existence of spatial effects, while the Wald test was used to determine whether the model would degenerate into the spatial lag model (SLM) or the spatial error model (SEM). Finally, the LR test was used to determine whether the spatial econometric model used individual fixed effects, time fixed effects, or two-way fixed effects.

The results of the spatial econometric model test are shown in Table 9, and all the results are significant at the 1% level, which verifies the correctness of the SDM model selection in this paper, so this paper finally chooses the two-way fixed effects spatial Durbin model (SDM) to test the impact of the digital economy on the efficiency of urban-rural integration.

Table 9. Test results of spatial econometric model selection.

Test	Statistic	p-value
Hausman	77.85	0.000
Spatial error:		
Moran's I	4.583	0.000
Robust Lagrange multiplier	302.546	0.000
Spatial lag:		
Lagrange multiplier	135.725	0.000
Robust Lagrange multiplier	15.364	0.000
Wald_spatial_lag test	54.81	0.000
Wald_spatial_error test	35.26	0.000
LR_spatial_lag test	70.13	0.000
LR_spatial_error test	78.34	0.000
Likelihood-ratio test (Spatial fixed inspection)	521.47	0.000
Likelihood-ratio test (Time-fixed inspection	5897.42	0.000

Based on the test results, this chapter chose to use the spatial Durbin model (SDM) with two-way fixed effects for regression analysis, and the regression results are shown in Table 10. Where columns (1)-(3) are the regression results of the spatial Durbin model with individual fixed effects, time fixed effects, and two-way fixed effects based on the adjacency matrix, respectively.

It can be seen that the spatial autoregressive coefficient of urban-rural integration efficiency is significantly positive and passes the test of significance at the 1% level, indicating that there is a significant spatial autocorrelation of urban-rural integration efficiency. Column (3) shows that the spatial spillover effect of digital economy on the efficiency of urban-rural integration is significantly positive, indicating that the improvement of the development level of digital economy can not only promote the urban-rural integration in the region, but also play a role in promoting the development of urban-rural integration in neighboring regions through the spatial spillover effect. In addition, the coefficient of the spatial lag term of openness (w* Open) is significantly negative, indicating that the increase in the degree of openness of the region may inhibit the efficiency of urban-rural integration in the neighboring cities, which is due to the fact that the growth of local foreign direct investment brings about the enhancement of industrial production technology and at the same time produces more and more crowding-out effects on the local traditional enterprises, and exacerbates the exodus of capital and labor factors from the neighboring regions, which has a negative impact on the development of urban-rural integration. This will have a negative spatial spillover effect on urban-rural integration. The coefficient of the spatial lag term of human capital (W*InHum) is significantly positive, indicating that the improvement of human capital in the region will promote the efficiency of urban-rural integration in the neighboring cities, and that the highly skilled people often have more choices in choosing jobs, which can accelerate the inter-regional labor mobility as well as the dissemination of knowledge and skills, thus generating a positive spatial spillover effect.

Table 10. Estimation results of Spatial Durbin Model.

Variable	Individual fixed effect	Time fixation effect	Bidirectional fixed effect
	(1)	(2)	(3)
Dige	0.0452* (1.92)	0.1843*** (17.04)	0.0518** (2.26)
Lm	0.0475*** (9.06)	0.2754*** (32.15)	0.0549*** (11.62)
Edu	0.0121 (0.91)	0.0759*** (4.17)	0.0058 (0.49)
Finadp	0.0031 (0.64)	-0.0025 (-0.46)	0.0078* (1.84)
Finance	-0.0015*** (-4.41)	-0.0010* (-1.74)	-0.0014*** (-4.47)
Open	-0.0148* (-1.85)	-0.0036 (-0.36)	-0.0139* (-1.78)
lnHum	-0.0061** (-2.25)	-0.0003 (-0.18)	-0.0051* (-1.92)
W**Dige*	0.2364*** (5.02)	-0.2316*** (-11.34)	0.2016*** (4.42)
W**Lm*	-0.0548*** (-5.67)	0.1327*** (7.35)	-0.0164 (-1.67)
W**Edu*	0.0367 (1.53)	0.0486 (1.39)	0.0253 (1.12)
W**Finadp*	-0.0241*** (-3.74)	-0.0099 (-1.52)	-0.0062 (-0.95)

W**Finance*	0.0003 (0.46)	-0.0052*** (-4.58)	-0.0004 (-0.48)
W**Open*	-0.0414** (-2.17)	0.0472* (1.75)	-0.0339* (-1.74)
W**lnHum*	0.0268*** (6.34)	0.0056*** (5.38)	0.0281*** (6.44)
rho	0.6065*** (35.81)	0.3272*** (12.01)	0.2614*** (9.75)
sigma2_e	0.0002*** (36.72)	0.0009*** (37.21)	0.0002*** (37.44)
Log-likelihood	8214.7506	5517.1639	8426.3142
R^2	0.1472	0.0038	0.0724

3.3.3. Decomposition of spatial spillover effects

The spatial spillover decomposition further analyzes the relationship between the effects of the digital economy on the efficiency of urban-rural integration across regions. The direct effect indicates the effect of changes in the level of digital economy in a region on the efficiency of urban-rural integration in that region. The indirect effect, i.e., the spatial spillover effect, indicates the effect of changes in the level of digital economy in neighboring regions on the efficiency of urban-rural integration in the local area. The total effect is the sum of the two, indicating the average effect of the digital economy on all areas in the region.

The results of the spatial spillover effect decomposition are shown in Table 11. The direct, indirect and total effects of the digital economy are all significantly positive at the 1% level, indicating that while the digital economy promotes the improvement of the efficiency of urban-rural integration in the region, it also effectively improves the efficiency of urban-rural integration in neighboring regions, which is consistent with the previous conclusion. The spatial spillover effect of the digital economy accounts for 80% of the total effect, indicating that the spatial spillover effect of the digital economy has become an important factor driving the development of urban-rural integration.

Table 11. Decomposition results of spatial spillover effects.

Variable	Direct effect	Indirect effect	Overall effect
Dige	0.0715*** (2.78)	0.2637*** (4.96)	0.3285** (5.62)
Lm	0.0541*** (11.75)	-0.0024*** (-0.21)	0.0525*** (3.83)
Edu	0.0091 (0.83)	0.0346 (1.24)	0.0437 (1.43)
Finadp	0.0081* (1.77)	-0.0063 (-0.82)	0.0019 (0.24)
Finance	-0.0015*** (-4.72)	-0.0008 (-92)	-0.0021** (-2.48)
Open	-0.0163** (-2.05)	-0.0478* (-1.96)	-0.0625** (-2.27)
lnHum	-0.0037 (-1.31)	0.0345*** (6.44)	0.0303*** (5.52)
Urban fixed effect	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes
Log-likelihood	8426.3142	8426.3142	8426.3142
R^2	0.0724	0.0724	0.0724

3.3.4. Robustness Tests

In order to ensure the accuracy and reliability of the research conclusions, this paper uses the geographic distance matrix to replace the adjacency matrix to verify the spatial spillover effect of the digital economy on the efficiency of urban-rural integration again. The selection of spatial measurement model is carried out first, and the results of the model selection test are shown in Table 12. It can be seen that under the geographic distance matrix, the same spatial Durbin model under the individual time two-way fixed effects should be selected for the spatial spillover effect analysis.

Table 12. Selection and verification results of spatial econometric models.

Test	Statistic	p-value
Hausman	193.74	0.000
Spatial error:		
Moran's I	37.526	0.000
Robust Lagrange multiplier	1241.530	0.000
Robust Lagrange multiplier	895.364	
Spatial lag:		
Lagrange multiplier	321.752	0.000
Robust Lagrange multiplier	56.414	0.000
Wald_spatial_lag test	27.96	0.000
Wald_spatial_error test	32.15	0.000
LR_spatial_lag test	39.69	0.000
LR_spatial_error test	44.52	0.000
Likelihood-ratio test (Spatial fixed inspection)	20.28	0.032
Likelihood-ratio test (Time-fixed inspection	6187.56	0.000

The results of choosing the geographic distance matrix to replace the adjacency matrix for the robustness test are shown in Table 13. It can be found that the estimation results based on the geographic distance matrix are not significantly different, and the direct effect of the digital economy on the efficiency of urban-rural integration as well as the spatial spillover effect are both significantly positive, which again indicates that the digital economy promotes the improvement of the efficiency of urban-rural integration in the region and at the same time promotes the development of urban-rural integration in the neighboring cities, and the regression results are robust and reliable.

Table 13. Robustness test results.

	SDM model	
Spatial weight matrix type	Adjacency matrix	Geographical distance matrix
Dige	0.0518*** (2.24)	0.0658*** (2.78)
W**Dige*	0.2016*** (4.41)	0.9467*** (4.21)
Direct effect	0.0715*** (2.78)	0.0837*** (3.24)
Indirect effect	0.2637*** (4.96)	3.2016** (2.57)
Overall effect	0.3285** (5.62)	3.2674** (2.63)
Control variable	Yes	Yes
rho	0.2635*** (9.79)	0.6854*** (7.95)
sigma2_e	0.0002*** (37.24)	0.0002*** (37.68)
Log-likelihood	8426.3142	8409.2467
R^2	0.0724	0.1914

3.4. Analysis of regional heterogeneity

In order to examine the impact of digital economy on the spatial spillover effect of urban-rural integration brought about by differences in location characteristics, the whole sample was divided into eastern, central and western, central and peripheral cities for regional heterogeneity analysis, and the results of regional heterogeneity analysis are shown in Table 14.

The direct and spatial spillover effects of the digital economy on urban integration efficiency in the eastern region are both significant at the 1% level, indicating that in eastern China, the digital economy not only promotes the efficiency of urban-rural integration in local cities, but also promotes the urban-rural integration development of neighboring cities. As the economy of the eastern region is more developed, the overall level of digital economy competitiveness is higher, and the level of development among cities is relatively balanced, which can accelerate the flow of high-skilled talents among regions. The direct effect of the digital economy on urban integration and the spatial spillover effect in the central and western regions are not significant, due to the low degree of development in the central and western regions, which is limited by a variety of factors that lead to an imbalance in the development of the digital economy, and the enhancement of the efficiency of urban-rural integration of the digital economy has not been fully manifested. The digital economy of the central city can significantly promote the efficiency of urban-rural integration in the region, but the promotion effect on peripheral cities is not significant, indicating that the central city has insufficient radiation driving effect on the periphery, and the level of synergistic development needs to be improved. The relatively slow development of peripheral cities and the general phenomenon of spillover of talent resources can improve the efficiency of urban-rural integration in peripheral cities, but the promotion effect on local urban-rural integration development is not obvious.

Table 14. Results of regional heterogeneity analysis.

Variable	The eastern region	Central and western regions	Central city	Peripheral cities
	(1)	(2)	(3)	(4)
Dige	0.1124*** (2.76)	0.0208 (0.64)	0.1120** (2.42)	-0.0425 (-0.97)
W**Dige*	0.2187*** (3.21)	-0.0825 (-1.09)	0.0481 (0.57)	0.1425** (2.01)
Direct effect	0.1253*** (3.24)	0.0196 (0.61)	0.1172** (1.84)	-0.0328 (-0.75)
Indirect effect	0.2813*** (3.72)	-0.0954 (-1.26)	0.0079 (0.87)	0.1621* (2.04)
Overall effect	0.3914*** (4.82)	-0.0692 (-0.87)	0.1247** (-2.61)	0.1245 (-1.54)
Control variable	Yes	Yes	Yes	Yes
rho	0.2285*** (4.57)	0.1304*** (3.45)	0.2065* (1.85)	0.2137*** (7.71)
sigma2_e	0.0003*** (21.57)	0.0002*** (26.83)	0.0004*** (14.21)	0.0002*** (34.85)
Log-likelihood	2567.4142	4672.0183	957.2430	7741.8360
R^2	0.1758	0.0002	0.0478	0.0465

4. Conclusions and strategic recommendations

In order to deeply portray the impact of digital economy on urban-rural integration efficiency, this study systematically measures the digital economy and urban-rural integration efficiency of 30 sample provinces in China from 2015 to 2024, and applies the kernel density estimation methodology to deeply reveal the temporal evolution characteristics and spatial differences of the digital economy and urban-rural integration development at the national level and the regional level, respectively. On this basis, a spatial econometric model is applied to empirically test the impact of digital economy on urban-rural integration efficiency and further reveal the heterogeneity of this impact at the regional level. The main conclusions are as follows:

(1) The unbalanced contradiction of China's digital economy development is more prominent, showing the characteristics of strong in the east and weak in the west, with the center in the middle, and the gap between the level of digital economy development of provinces within the eastern and western regions is gradually obvious.

(2) The level of China's urban-rural integration and development has increased in the midst of fluctuations, and has shown significant regional differences, with the spatial characteristics of "high in the east and low in the west".

(3) There is a significant positive spatial spillover effect of the digital economy on the improvement of urban-rural integration efficiency, indicating that the development of the digital economy in this region not only promotes the urban-rural integration development of this city, but also effectively promotes the improvement of the urban-rural integration level in the neighboring regions, which becomes an important factor for the digital economy to drive the development of urban-rural integration.

Based on this, this paper puts forward the following strategic suggestions:

(1) Make full use of the connecting role of the digital economy to promote the linked development of the urban-rural industrial chain.

(2) Strengthen the construction of digital infrastructure and promote the deep integration of digital technology and the real economy.

(3) Strengthen the construction of digital culture in rural areas and cultivate the digital literacy of rural residents.

(4) Combine the characteristics of unbalanced development of the digital economy, and implement measures according to local conditions and precision.

(5) Enhancing the level of regional economic development, improving the quality of employment for urban and rural residents, and improving the social security system.

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