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Spatial Characteristics and Driving Factors Toward the Digital Economy: Evidence from Prefecture-Level Cities in China

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Abstract

The digital economy is becoming an increasingly important source of regional competitiveness enhancement. The purpose of this research is to examine the spatial distribution characteristics of China's digital economy from 2016 to 2019. Moran's I analysis was performed to see if China's digital economy has spatial self-correlation. The Getis-Ord General G test was used to determine the clustering type of China's digital economy. In addition, we used OLS and GWR methodologies to figure out what drives China's digital economy level. The findings show that the digital economy is rapidly expanding throughout China; yet, there is a significant regional imbalance in the digital economy level in China, and the agglomeration of the digital economy is increasing over time. Furthermore, the findings reveal that human capital, information staff, telegram income, and Internet access are vital factors in the development of the digital economy. To close the digital economy gap, policymakers must invest in human capital and technology innovation. Simultaneously, the government must speed up the development and implementation of electronic information services.

Keywords: Digital Economy, Spatial Correlation, Driving Factors, Geographical Weighted Regression

JEL Classification Code: C19, C21, C13, C10

1. Introduction

The globe has entered the digital era as a result of the advancement of Information and Communication Technologies (ICT) technologies. A resilient world is defined by the digital economy's constant performance, and active digital activities strengthen our society's virtualization (Alzhanova et al., 2020; Sepehrdoust & Khodaee, 2013). As a result, a more constructive understanding of the existing state of the digital economy aids us in establishing a global information world (Zhang et al., 2021). Typically, the evolution of the digital sector has three characteristics: variety, diversity, and dynamism, all of which were thought to contribute to the study of the global economic and political system's complexity (Alibekova et al., 2020; Dwivedi et al., 2021; Mensah, 2019). Simultaneously, widespread employment and accessible access boost subversive and all-around innovation (Alibekova et al., 2020; Jiao & Sun, 2021).

However, there is still a large disparity in China's digital economic levels across the country. As a result, the goal of this research is to examine China's digital economy's spatial distribution and determine the root cause of the country's digital divide. According to studies, digital economic development in China's east and west regions has imbalanced characteristics. The digital economy has a direct impact on regional disparities. The digital economy is imbalanced, and China has launched a number of initiatives to close this regional gap and encourage regional coordinated development (Tang & Lu, 2021).

Some scholars have studied the spatial distribution of digital economic development. For instance, Zhong and Mao(2020) found that the level of the digital economy in the Yangtze River is low, and there is a hunch-like shape

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in spatial distribution. Binyan et al. (2018) showed that the level of digital economic development in China's Northeast regionlags behindthe national average,and the internal polarization is obvious. The differences in digital economic development in the Beijing-Tianjin-Hebei urban group are significantly higher than that of other urban groups, and urban group differences are the main source of their development. Moreover, China's digital economic development is distinguishedonaprovincial scale, presenting the characteristics of the east to west gradient, but the Sichuan and Yu become a new pole in innovation.

Existing studies have offered a good reference for this article, however, it is worth investigating further in the following three areas: First, there is literature on the development of China's digital economic level, which is based on provincial level statistics, although digital economic processes are more integrated into cities. As a result, the digital economic level's spatial distribution features will be more logical when compared to the urban level.

Second, most of the literature is studied in terms of the characteristics of digital economic level development in the research material, but there is very little research on the formation mechanism or influencing factors of digital economic level distribution. Third, many simple OLS regression methods have been used to analyze the influencing factors of human capital geographical distribution in the research method, but this method ignores the spatial heterogeneity and spatial dependency of the study object.

Based on this, the current study intends to reveal its spatial characteristics utilizing space-related analysis, GIS space expression, and a geographically weighted regression model to clarify China's urban human capital spatial distribution characteristics (GWR). The driving element serves as a benchmark for China's regional economic balance growth.

2. Methodology and Data

2.1. Research Method

2.1.1. Spatial Self-Correlation Analysis

Space self-correlation describes the overall spatial relationship of all units in the study space, usually using the Moran's I index to analyze some phenomena of adjacent areas (spatial positive correlation) or different (space negative), or Independence (random distribution), its calculation formula is:

$$I = n\sum_{i=1}^{n}\sum_{i=1}^{n} w_{ij}(x_i - \bar{x})(x_j - \bar{x}) \Bigg/ \left(\sum_{i=1}^{n}\sum_{i=1}^{n} w_{ij}\right)\sum_{i=1}^{n}(x_i - \bar{x})^2 \quad (1)$$

Where: X_i represents the observation value of the region i; N is the number of regions; W_{ij} is a spatial weight matrix to define the mutual adjacency of spatial objects. There are two main types of spatial weighting, one is based on the principle of neighboring relationships, and the other is based on the principle of distance. The unit studied in this paper is the prefecture-level city. Because of the prefecture-level city's adjacency, there is no adjacency unit in more cities due to a lack of data, making it unsuitable for selection based on neighboring relationships. Therefore, we should choose the principle based on distance principle Spatial weight settings and ensure that each unit has at least one neighbour 1. Generally, adjacent standards are adjacent to 1 in two regions, otherwise 0.

2.1.2. Getis-Ord General G

Getis-Ord The degree of local spatial aggregation of all units within the study space is described by general G analysis. Typically, the general G value and Z score value are used to analyze the spatial feature distribution, which is prone to high polymerization or cluster distribution, and the calculation formulas are as follows:

$$G = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{i,j} x_i x_j}{\sum_{i=1}^{n}\sum_{j=1}^{n} x_i x_j}, \forall j \neq 1 \quad (2)$$

Where: X_i represents the observation value of the region i; N is the number of regions; W_{ij} is the spatial weight matrix, used to define the mutual adjacency of the spatial object.

$$\mathrm{ZG} = \frac{G - E[G]}{\sqrt{V[G]}} \quad (3)$$

Among them, the calculation formula of A and B is as follows:

$$E[G] = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{i,j}}{n(n-1)}, \forall j \neq 1$$
$$V[G] = E[G^2] - E[G]^2 \quad (4)$$

2.1.3. Geographical Weighted Regression (GWR) Analysis

$$y_i = \beta_0(\mu_i, v_i) + \sum_{j=1}^{k} \beta_j(\mu_i, v_i) x_{ij} + \varepsilon_i \quad (5)$$

Where: y_i is an interpreted variable; β_0 is a constant term, which performs a local regression estimate by using

sub-sample data information of adjacent observations; (μ_i, v_i) is a geographic location coordinate of observed sample i; ε_i is a random error of region i; The subscript j is a $K + 1$ function of the geographic location (μ_i, v_i); $\beta_j(u_i, v_i)$ is the elastic coefficient of the region i. Estimation of any regional feature elasticity in the study adopts the weighted least squares method, and the estimated value is as follows:

$$\hat{\beta}(u_i, v_i) = \left[X^T W(u_i, v_i) X^{-1} X^T W(u_i, v_i) Y \right] \tag{6}$$

Where: X is explained the variable matrix; $W(\mu_i, v_i)$ is the spatial weight matrix, which is composed of the monotonous delivery function of the geographic distance between the regression zone and its neighboring region. And the GUAs function usually represented $W(\mu_i, v_i)$:

$$W(\mu_i, v_i) = \exp[-(-d_{ij}/b)^2] \tag{7}$$

Where: d_{ij} is the distance between the zone i and the area j; b is the optimal bandwidth, determined by the Minimum Information Guidelines (AIC). The advantage of the GWR model is that the advantage of the GWR model is: (1) GWR can solve the space self-related problem while the OLS model cannot solve; (2) Each sample spatial unit in GWR models provides a coefficient estimate, allowing the model outcome to better represent local conditions. (3) GWR can reveal the spatial differences and how these work.

2.2. Variable Settings and Data Sources

Because the digital economy is essentially a fusion of the old economy and Internet technology, it is influenced by a wide range of elements. Economic development, industrial structure, human capital level, innovation capacity, information infrastructure, and information utilization, according to (Zhang et al., 2020; Zhong & Mao, 2020), may have a major impact on the regional difference in digital economic development. The following explanations will clarify how these parameters work and how we measure them in our study:

(1) Economic development condition: The digital economy is inextricably linked to its economic foundation as a result of the traditional economy and data resources. Strong economic growth can have a direct impact on the development of digital infrastructure. The share of area GDP in national GDP is used in this study to indicate local economic conditions (Gaziz et al., 2020).
(2) Industrial structure: The digital economy is intertwined with the first, second, and third industries, with the third being particularly important due to retail e-commerce. To measure the industrial structure, we use the gravity of the third industry accounts for local GDP (Zimmermann & Koerner, 1999).
(3) Human capital level: The competitiveness of individuals is at the core of the city's competitiveness. Regions with high human capital can promote information communication and attract greater labor inflows due to positive externalities. As a result, this study follows Arauzo-practice Carod's of using the proportion of students at a school accounting for the total number of ordinary colleges as a proxy variable for human capital. (Arauzo-Carod, 2021).
(4) Technological innovation capabilities: Because regional digital economic development is unaffected by science and technology support, this study uses technical patent authorization as a proxy variable (Hanna, 2018).
(5) Information infrastructure level: The digital economy benefits from a high level of information infrastructure. The intensity of regional information infrastructure is reflected in the level of information infrastructure, which demonstrates its future development potential (Williams, 2021). As a result, this study uses information industry employees and telecom income to represent this variable.
(6) Information utilisation level. Digital information has the potential to significantly increase the popularity of digital technology, which, in turn, will fuel the growth of the digital economy. As a result, we have used mobile phone access and Internet access as metric instruments. So, how do we track the progress of the digital economy? The use of a standard to construct this indicator is a common method (Nenkina, 2020), but it is not objective enough. Data from the Tencent Institute's China Internet Digital Economic Index from 2016 to 2019 and the China City Statistical Yearbook 2019 are used in this analysis. Table 1 shows descriptive statistics for model variables.

2.3. Analysis of Spatial Characteristics of Digital Economy Level in the Prefecture-Level City

2.3.1. Digital Economic Agglomeration is Further Enhanced

Furthermore, 13 cities from the eastern region, three from the middle, four from the western section, and none from the northeast make up the top 20 cities with the highest digital economy levels. While the east region only accounts for one of the twenty cities with the lowest digital economy level, In 2019, the level of digital economic development in China's locations is depicted in Figure 1. The digital economy

Table 1: Descriptive Statistical Analysis of Variables

Variables	obs	Mean	Std.	Min	Max
Digital economy	254	3.685	6.432	0.044	39.596
Per gdp	254	6.213	3.497	1.443	19.194
Industrial structure	254	62.27	256.94	26.54	4139
Human capital	254	0.812	1.599	0.012	12.35
innovation	254	1.552	6.444	0.04	84.03
Information staff	254	4.934	7.179	0.14	61.933
Telegram income	254	5.35	5.705	0.32	40.09
Telephone access	254	14.298	14.387	0.1	127.4
Internet access	254	2.122	3.641	0.282	35.734

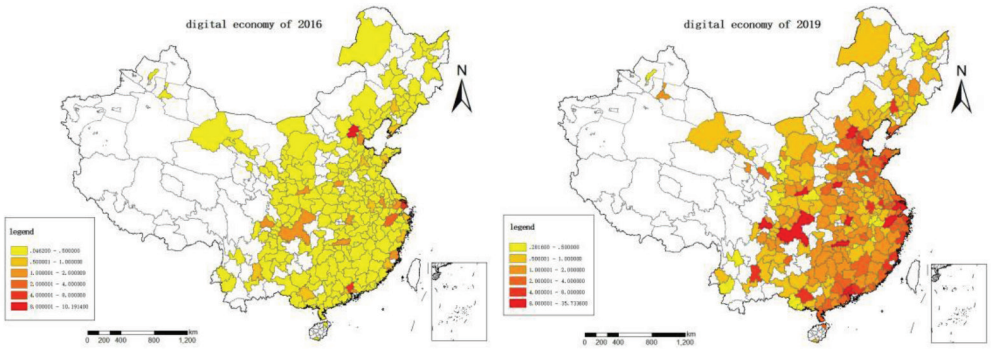


Figure 1: Digital Economy Index of China's Prefecture-Level Cities

is exhibiting a clear spatial evolution. First, the degree of digital economic aggregation in the east has increased, but considerable differences exist across the three major regions, namely the east, the middle, and the western regions. The Bohai area, the Yangtze River Delta, and the Pearl River Delta are the most visible agglomerations.

2.3.2. Digital Economic Development Levels in The Region Are Significant

Taking *z* digital economy in 2019 as an example, Beijing has the highest level of digital economic development (35.7336), 127 times the lowest level of digital economic development (0.2816) in Jinchang. Beijing, Shanghai, Guangzhou, Shenzhen, Dongguan, Chengdu, Chongqing), and 15 cities with digital economic development below 0.2 (Ali Zhi, Changdu, GuLuzhou, Haibei, Hainan) State, Kizilu Kirgiz, Linzhi, Naqu Region, Qianjiang City, Shigan District, Shannan, Shennongjia District, Tianmen City, Yushuzhou).

Furthermore, 13 cities from the eastern region, three from the middle, four from the western section, and none from the northeast make up the top 20 cities with the highest digital economy levels. While the east area only accounts for 1,5 cities from the central region, six cities from the Northeast, and eight cities from the western region among the 20 cities with the lowest digital economy level. In this regard, China's digital economy has increased significantly in the eastern area, with key cities such as Beijing, Shanghai, Guangzhou, and Shenzhen leading the way. In each city, there are still significant differences in digital economic levels.

2.3.3. Digital Economic Development Presents a Significant Space Positive

According to the neighbor relationship among cities, the binary adjacency matrix is established. We calculate Moran's I and general values based on the matrix using ArcGIS10.5 software. The 2019 digital economy's Moran index and *Z* score are 0.1231 and 4.5950, respectively. And the *p*-value is 0.0000, indicating that the test was passed at a 1% significance level. At the same time, the digital economy's *G* value and *Z* score for 2019 are 0.000001 and

4.8430, respectively. The *P*-value is 0.0000, which means the test passes at a 1% significance level.

2.4. Factors Affecting the Level of Digital Economic Development

2.4.1. OLS Model and Drive Factor Selection

The variables in the ArcGIS platform were treated with the step-by-step regression model, and those with a VIF value larger than 5 were excluded. Human capital, information staff, telecommunications income, and Internet access were the last four interpretation variables. (See Table 2) The regression model $R^2 = 0.9269$ now has a better fitting performance.

The VIF values of telephone access and innovation in Table 2 are the highest; we removed these two indicators first, then ran OLS regression again, based on the concept of caution. This time, all explanatory variable VIF values are less than 5 (Table 3).

The OLS regression result of industrial structure and per capita GDP is not significant at a 5% significance level (Table 3). As a result, we removed these two markers and ran the OLS regression again. Table 4 displays the results. Table 4 shows that these four variables, such as human capital, information staff, telecom income, and Internet access, meet the GWR conditions well, irrespective of their value or robust *p*-value. As a result, these four factors are applied to the GWR return.

Table 2: OLS Regression with All Explanatory Variables

Variables	Coefficient	*T* value	*P* value	Robust_Pr [b]	VIF
Cons	−0.001384	−0.608730	0.543245	0.339065	–
Hum	0.049828	4.239345	0.000036*	0.040267*	3.013991
Str	−0.005545	−0.760276	0.447781	0.348942	1.861584
Per gdp	0.004119	0.228714	0.819274	0.029192*	1.015277
Inno.	0.184388	8.408287	0.000000*	0.000000*	6.624183
staff	0.383224	14.856800	0.000000*	0.000000*	3.169727
Income	0.116039	5.251398	0.000001*	0.053599	5.523683
TA	0.361252	12.610498	0.000000*	0.000000*	14.647421
IA	−0.163338	−6.800568	0.000000*	0.003760*	6.527258

Table 3: OLS Regression After Deleting the Two Explanatory Variables with the Largest Expansion Factor

Variables	Coefficient	*T* value	*P* value	Robust_Pr [b]	VIF
Cons	−0.003490	−1.150182	0.251131	0.092354	–
Hum	0.101449	6.102524	0.000000*	0.024359*	2.524561
Str	0.015564	1.511810	0.131818	0.166078	1.552901
Per gdp	−0.002089	−0.075169	0.940126	0.552352	1.012286
Staff	0.556291	15.170094	0.000000*	0.000000*	2.682248
Income	0.312336	10.369504	0.000000*	0.004149*	4.297376
IA	0.124627	4.626558	0.000008*	0.038584*	3.437648

Table 4: OLS Regression after Deleting Explanatory Variables with Insignificant Coefficients

Variables	Coefficient	*T* value	*P* value	Robust_Pr [b]	VIF
Cons	−0.000576	−0.246800	0.805261	0.725374	–
Hum	0.105871	6.466033	0.000000*	0.018624*	2.446220
staff	0.550461	15.087629	0.000000*	0.000000*	2.652107
Income	0.320365	10.799179	0.000000*	0.003235*	4.163840
IA	0.131132	4.928818	0.000002*	0.035802*	3.349618

2.4.2. Drive Factor GWR Model Regression

In ArcGIS10.5 software, the adaptive core function is used to achieve a minimum AICC bandwidth. Table 5 shows the GWR regression's estimation results. The GWR model outperforms the OLS model by a large margin, and the GWR model's AICC (−1201.9702) is lower than the OLS model's AICC (−1147.5271). The modified R^2 value also changed from 0.9269 to 0.9420. As a result, we feel the GWR model's interpretation capability has been improved. Each spatial unit in the GWR model has its own coefficient. Table 6 presentsa descriptive statistical analysis of the regression coefficient of the GWR model. The results reveal that partial variable regression coefficients are unstable. Because the maximum and minimum levels of information staff and Internet access point in the same direction, we assume that having more information staff or having higher Internet access in China indicates having a greater level of thedigital economy. In comparison, the maximum and minimum levels of human capital and telecom income do not have the same direction, indicating that higher levels of the digital economy in China are not always associated with higher levels of human capital and telecom income. However, positive relationships exist in most cities.

2.5. Analysis of Space Mode of Drive Factor

(1) The role pattern of human capital: As shown in Figure 2a, the regression coefficient of human capital decreases from west to east. Southwest has a high value, while most of the Northeast has a low-value regression coefficient. This conclusion shows that whereas human capital has a high marginal utility in the west, and a low marginal utility in the eastern region, particularly in the northeast.

(2) The role pattern of information staff: Figure 2b shows that in the northern regions, such as Beijing, Tianjin, Hebei, Shanxi, and others, the information staff regression coefficient has a high value. While for southwest information staff regression coefficient has a low value. The findings suggest that robust information infrastructure can help the north improve its digital economy development.

(3) The role of telecom income: Figure 2c shows that the regression coefficient of telecom income is the lowest in the western area, indicating that telecom income hasn't been an essential engine for the development of the local digital economy, whereas it has become an impetus to encourage local development in the other regions.

(4) The role of Internet access: Figure 2d demonstrates that, despite being in the southwest, the regression coefficient is high. This conclusion shows that throughout most of China, the marginal utility of internet connectivity is very high. As a result, by popularizing the Internet, the government may help to develop a digital economy.

Table 5: Parameter Estimation and Test Results of GWR Model

Parameters	Value
Bandwidth	9.0954
ResidualSquares	0.1451
EffectiveNumber	21.0056
Sigma	0.0244
AICc	−1201.9702
R^2	0.9464
R^2 Adjust	0.9420

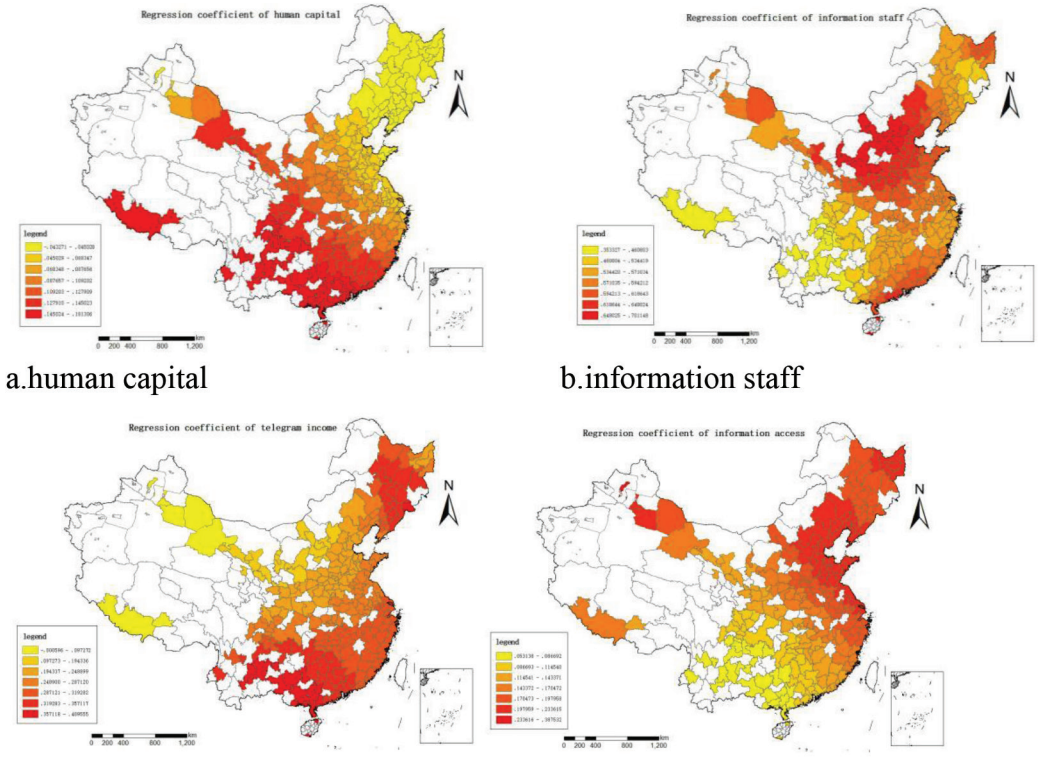
3. Conclusion and Policy Recommendations

This study explores the spatial characteristics and the driving factors of digital economy development, which provide a reference for perfecting China's digital industrial distribution and narrowing digital gaps. We used Moran's I analysis to see if China's digital economy had spatial self-correlation. The Getis-Ord General G test was used to determine the clustering type of China's digital economy. We used OLS and GWR approaches sequentially to determine the driving variables of China's digital economy level.

On the one hand, the data show that the digital economy is rapidly expanding throughout China; on the other hand, there is a significant regional gap in the digital economy

Table 6: Descriptive Statistical Analysis of Regression Coefficient of GWR Model

Variables	Mean	Min	25%	Mid	75%	Max
Hum	0.0975	−0.0433	0.0624	0.0992	0.1370	0.1813
Staff	0.5783	0.3533	0.5663	0.5832	0.6813	0.7011
Income	0.2726	−0.0006	0.2381	0.2861	0.3161	0.4096
IA	0.1564	0.0592	0.1189	0.1628	0.1950	0.3875



a.human capital b.information staff

a. human capital b. information staff

c. telecom income d. internet access

Figure 2: Spatial Distribution of the Regression Coefficients

level in China, and digital economy agglomeration is increasing over time.Furthermore, the findings reveal that human capital, information staff, telegram income, and Internet connection are the most critical factors in accelerating the development of the digital economy. They fulfill different roles in different locations at the same time. As a result, governments in the West must continue to improve the level of human capital and technology innovation to close the digital economy deficit. In the northern part of the country, the government may boost the digital economy by encouraging more individuals to work in the information sector. At the same time, in the east, increasing telecom income and popularizing the Internet would be more helpful.

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