Social Sciences & Humanities in Asia (SSHA)

DOI:http://doi.org/10.65098/ssha.01.2025.18.32

CODEN: SSHAGX

RESEARCH ARTICLE

DIGITAL ECONOMY, PROXIMITY AND REGIONAL INNOVATION CAPABILITY—— EMPIRICAL RESEARCH BASED ON THE PERSPECTIVE OF COLLABORATIVE INNOVATION

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ARTICLE DETAILS

Article History:

Received 22 Aug 2025
Accepted 29 Sep 2025
Available online 17 Oct 2025

Online Article Code

ABSTRACT

Background and Purpose: With fraud losses expected to reach USD 41 billion by 2027, the swift growth of digital finance has increased the dangers associated with international payment networks. According to reports, 72% of financial institutions have seen an increase in attempts at fraud. This study combines financial analytics, cybersecurity, and behavioral economics to create a real-time, adaptive fraud prevention system since it acknowledges that no single technology can eliminate these risks. By addressing both systemic and human vulnerabilities, the goal is to increase the resilience of the financial system.

Methods: Behavioral nudges, adaptive AI algorithms, and real-time transaction analysis were all combined to create a hybrid system. Key cognitive biases that make people vulnerable to fraud were uncovered by the study, including overconfidence, loss aversion, hyperbolic discounting, and the familiarity heuristic. More than 10,000 anonymous bank transactions from the US, Japan, and India were used to test a prototype. To fortify defenses, the architecture integrated situational threat intelligence and Zero Trust security model concepts.

Results: Compared to previous models, the method increased the accuracy of fraud detection by 27% and decreased false alarms by 18%. Adaptive security techniques combined with behavioral insights greatly decreased algorithmic and human error. Early risk identification and user engagement were improved by its human-centered design, which included individualized learning prompts, decision aids, and real-time notifications.

Conclusion: The results highlight how behavioral economics and advanced analytics can be combined to improve cybersecurity and digital banking. Financial institutions are better equipped to manage changing digital risks thanks to this cross-disciplinary, data-driven approach. With useful ramifications for legislators, cybersecurity professionals, and financial institutions alike, the study emphasizes the significance of combining human behavioral aspects, adaptive machine learning, and Zero Trust security principles to combat payment fraud.

KEYWORDS

Digital Economy, Proximity, Regional Innovation Capability, Collaborative Innovation

1. INTRODUCTION

Digital economy is the main economic form after agricultural economy and industrial economy, and it is the most distinctive feature of economy and society in the new era. According to the "China Digital Economy Development Report (2023)" issued by the China Information and Communications Institute, in 2022, the scale of China's digital economy will reach 50.2 trillion yuan, accounting for 41.5 % of GDP, forming a common development pattern driven by service industry and industrial digitization, which makes China's regional innovation ability rapidly improved. Digital economy has a strong spatial effect of innovation spillover, and proximity is an important factor affecting spatial spillover effect (Chen et al., 2022). Therefore, digital economy and proximity are two key factors affecting regional innovation ability. In the early days, due to the relatively low level of productivity development, proximity was regarded as one of the most important factors of economic development, and more attention was paid to the role of geographical proximity, and then the focus gradually shifted from geographical proximity to other proximity (Etzkowitz & Leydesdorff, 2000). However, it is undeniable that the rapid development of the digital economy has indeed brought a certain impact on the role of proximity. With the increasing complexity of human economic and social life and the increasingly wide range of activity space, especially the rapid development of information technology, geographical proximity, as one of the factors affecting inter-regional innovation linkages, has evolved into a necessary condition for innovation spillover, and its importance is weakening. Innovation diffusion is increasingly affected by related factors such as technological proximity and institutional proximity (Boschma, 2005).

At present, the related research mainly focuses on the relationship between digital economy and regional innovation capability (Kastelli et al., 2024), the relationship between proximity and regional innovation network (Golra et al., 2024; Jun et al., 2022). In terms of digital economy and regional innovation capability, the current research mainly focuses on whether there is a threshold benefit of digital economy in the process of improving regional innovation capability (Dong et al., 2024), and how to better play the spatial spillover effect of digital economy (Zhou & Guo, 2024; Zou et al., 2024), most scholars believe that digital economy can enhance regional innovation capability through which mediating variables affect regional innovation capability (Xu and Li, 2025). In terms of proximity and regional innovation network, because proximity is generally characterized by matrix, regional innovation network can also be characterized by matrix, so there are many studies on the relationship between them (Wilke & Pyka, 2025; Sheng & Ding, 2024; Errico et al., 2024), and the QAP method is mostly used, but it cannot have a direct connection with the variables of digital economy and regional innovation capability. Therefore, the research on the relationship between proximity and regional innovation capability is extremely rare. Due to the gap between research methods, the two closely related variables of digital economy and proximity cannot appear in the same academic paper at the same time.

Based on this, this paper puts the digital economy, proximity and regional innovation capability under the same analytical framework, and there may be the following two innovations: the first is the innovation of research methods. On the basis of the benchmark regression of digital economy and regional innovation capability, the spatial weight matrix is constructed, the variable of proximity is introduced, and the spatial Durbin model is applied to study the relationship between the three. Secondly, new variables are introduced. Based on the theory of regional innovation system, the variable of collaborative innovation is introduced, and relevant indicators are constructed. The possible relationship is analyzed by moderating effect to make up for the shortcomings of relevant empirical research. Compared with the existing research, this paper tries to make contributions in the following aspects: First, in the context of the rapid development of the digital economy, it tries to answer whether proximity is still important and what kind of proximity is more important; secondly, how can we better play the role of digital economy and proximity to enhance regional innovation capabilities and thus enhance China's international competitiveness. Based on this, this paper first studies the relationship between digital economy and regional innovation capability, then uses the spatial Dubin model to increase the impact of multi-dimensional proximity, and studies how proximity and digital economy interact with regional innovation capability from two aspects of direct and indirect effects. Finally, the moderating effect of collaborative innovation is discussed.

2. RESEARCH HYPOTHESIS

2.1 Digital Economy and Regional Innovation Capability Improvement

Since the father of the digital economy, Don Tapscott, proposed the digital economy, the digital economy has gradually become characterized by digital empowerment and innovation diffusion. Although the digital economy is characterized by capital, knowledge and technology intensity, it is faced with the uncertainty pressure of market winner-take-all and accelerating technological iteration. Ding et al. (2022) found that the digital economy has a threshold effect on improving regional innovation capabilities. Only when the digital economy and regional innovation development match to a certain extent, can regional innovation capabilities be improved. Liang & Li (2023) believe that there are two thresholds for the scale of digital economy development. The promotion of digital economy on regional innovation capability shows the nonlinear law of decreasing marginal effect first and then increasing marginal effect. Spatial correlation is an important factor for digital economy to promote high-quality development. Chen et al. (2021) believed that although the development of digital economy may have a negative impact on the economic resilience of local or neighboring regions in the short term, it has a significant positive impact in the long run. The digital economy has promoted economic globalization, making the economic ties between different regions closer, which is conducive to integrating the regional economy into a whole. It has the effect of "one loss and one prosperity" in a certain region, and plays the role of economies of scale and economies of scope. It has been recognized by scholars that digital economy can improve regional innovation ability. It is further proposed that:

H1: Digital economy has a positive effect on regional innovation capability.

2.2 Proximity and Regional Innovation Capability Improvement

A beggar-thy-neighbor or a companion? Geographical proximity is still the preferred element in the study of proximity. In the early days of human society, due to the limited scope of activities, communication and cooperation between people were limited to small geographically adjacent areas, and geographical proximity was the absolute influencing factor of economic and social activities. As early as the 1990s, with the development of information and communication technology and the digital economy, economists such as Richard and Cairncross began to explore the issues of "geographical end" and "distance death" brought about by ICT and innovation networks. The rise of the digital economy has caused a certain impact on geographical proximity, breaking the traditional space-time constraints and weakening the boundaries of regional innovation. The innovation output of a region is not only related to the R&D investment of the region itself, but also closely related to the R&D activities of other adjacent or even non-adjacent regions. Based on Rogers innovation diffusion theory, innovation will bring regional economic growth and income increase through horizontal and vertical diffusion in a wide range. At the same time, innovation does not spread evenly to all other regions, and there is a certain threshold for knowledge spillovers between regions with different innovation capabilities. Greunz (2003) believes that various types of proximity have an important impact on innovation spillovers, and are not independent of each other, but overlap. The concept of proximity originated from the study of industrial clusters. In the 1990s, the French proximity dynamics school pointed out that in addition to geographical proximity, other forms of proximity may contribute to interactive learning and innovation, which indicates that scholars attention to proximity began to shift from a single geographical proximity to multi-dimensional proximity. Furthermore, Boschma constructs the classification method and analysis framework of the five dimensions of institutional proximity, geographical proximity, social proximity, cognitive proximity and organizational proximity. In summary, the following hypotheses are proposed:

H2a: The effect of digital economy on regional innovation capability is affected by spatial distance.

H2b: The effect of digital economy on regional innovation capability is affected by spatial geographical adjacency.

H2c: The effect of digital economy on regional innovation capability is affected by spatial economic proximity.

H2d: The effect of digital economy on regional innovation capability is affected by spatial technology proximity.

2.3 The Moderating Effect of Collaborative Innovation

Philip Cook first proposed the concept of regional innovation system, but later research mainly focused on the qualitative research of regional innovation system, or based on the research of some countries with more developed market economy in Europe and the United States, which lacked both qualitative research and localization application in China. The regional innovation system generally refers to the coordination between government innovation policies, universities, scientific research institutions, enterprises and intermediaries within a certain region, to promote scientific research, technological innovation, and ultimately achieve a good state of industrialization of emerging technologies. In essence, it is a process of institutionalization and proceduralization of various innovation rules to achieve localization. Di et al.(2021) believed that regional collaborative innovation is the most fundamental goal of the construction of regional innovation system, and subject collaboration and regional collaboration are the two most important ways of collaboration, which are ultimately to promote the transfer and transformation between science, technology and industry. In order to accurately evaluate the impact of digital economy on regional innovation capability, each region cannot be regarded as an independent individual, but must take into account the spatial correlation between regions (Wang et al., 2022). At the same time, in the process of collaborative innovation, scientific research ability, technological innovation ability and industrial innovation ability, as the three stages of innovation, may have synergistic and crowding-out effects (Yu et al., 2013), while basic research, applied research and experimental development investment are the specific measures of the three stages. In summary, based on the theory of regional innovation system, taking collaborative innovation as a moderating variable, the following hypotheses are proposed:

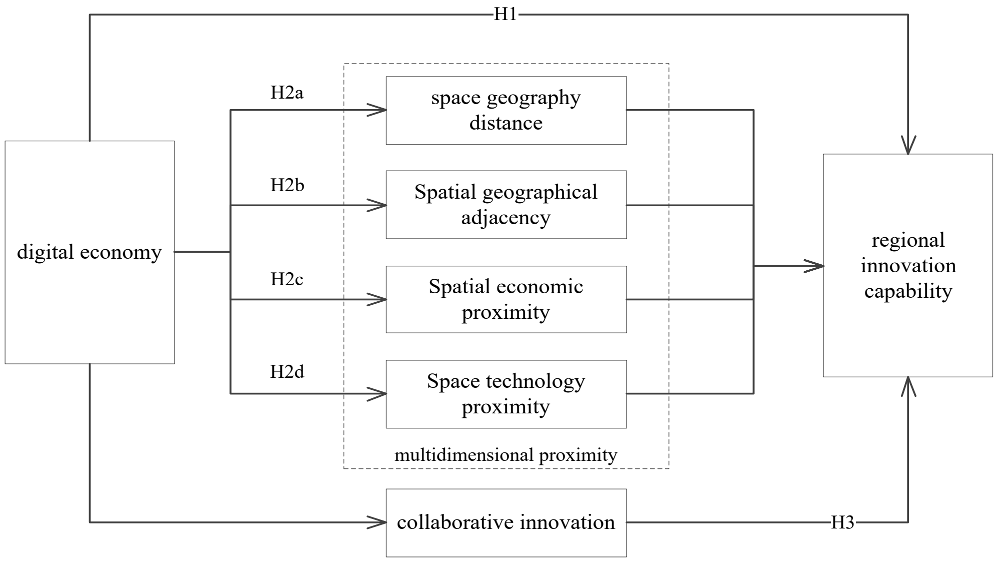

Figure 1: Logical Framework Diagram

H3: Collaborative innovation positively regulates the impact of digital economy on regional innovation capability under different proximity conditions.

3. MODEL DESIGN AND VARIABLE SELECTION

3.1 Definition of Variables

3.1.1 Explained Variable: Regional Innovation Capability (RIA)

Based on the relevant research of Tian et al. (2023), Su et al. (2021), Wang & Chen (2024), Cheng et al. (2023), this paper selects the number of scientific papers, the total amount of technology contract transactions, the number of patent application authorizations, and the sales revenue of new products of industrial enterprises above designated size to measure the regional innovation capability. Because the entropy weight method can consider the correlation between the indicators and take into account the differences between the indicators, and the operation is simple and not affected by subjective factors, it is suitable for multi-criteria decision-making problems. Therefore, the entropy weight method is used to determine the weight of each secondary index (see Table 1), and the regional innovation capability index values of each province from 2011 to 2021 are further calculated as the explanatory variables of this paper.

3.1.2 Explanatory Variables: Digital Economy (DE)

Based on the research of Pan et al., (2022), the development level of digital economy is measured from three dimensions: digital infrastructure, industrial digitization and digital industrialization. Among them, digital infrastructure is measured by cable line length and mobile phone penetration rate, industrial digitization is measured by online mobile payment level and information transmission, software and information technology service industry practitioners, and digital industrialization is measured by digital financial digitization. The digital economy also uses the entropy weight method to standardize the five three-level indicators, and obtains the scores of the digital economy development of each province from 2011 to 2021 (see Table 2).

3.1.3 Spatial Weight Matrix

There are many overlapping and overlapping parts among the concepts

Table 1: The Weight of Each Index of Regional Innovation Ability

First Grade Indexes	Second Index	Weight
Regional Innovation Ability (RIA)	Number of scientific papers (SCI) (papers)	0.185
	Total turnover of technical contract (ten thousand yuan)	0.339
	Number of patent application authorizations (pieces)	0.246
	New product sales revenue of industrial enterprises above designated size (ten thousand yuan)	0.230

Table 2: Weights of Each Index of Digital Economy

First Grade Indexes	Second Index	Third grade indexes	Weight
Digital Economy (DE)	Digital Infrastructure	Fiber optic cable line length (km)	0.104
		Mobile phone penetration rate (per 100 people)	0.044
	Industrial Digitalization	Online mobile payment level (-)	0.626
		Number of employees in information transmission, software and information technology services (10,000)	0.182
	Digital Industrialization	Digitization degree of digital finance (-)	0.044

of proximity, which requires researchers to make targeted choices. Before conducting spatial correlation analysis, it is necessary to establish a spatial weight matrix. Different spatial weight matrices can conduct in-depth research on different proximity problems. This paper chooses to construct four different spatial weight matrices, namely inverse distance weight matrix, spatial adjacency matrix, spatial economic distance matrix and spatial technology matrix.

(1) Inverse distance weight matrix

The inverse distance weight matrix mainly measures the relationship between the distance between spatial units and the spatial effect (Zhang et al., 2021). Generally, the spatial effect is positively correlated with the distance. Through the analysis of the inverse distance weight matrix, it is explored whether the two provinces are not adjacent to each other, but whether they will have a more significant spatial effect because of the relatively close distance. The formula is as follows:

$$W_{inv} = \begin{cases} 0, i = j \\ \frac{1}{d_{ij}}, i \neq j \end{cases} \quad (1)$$

Among them, $\frac{1}{d_{ij}}$ is the reciprocal of the geographical distance between the provinces of i and j, W_{inv} the smaller the distance between the two provinces, the greater the distance between the two provinces.

(2) Spatial adjacency matrix

The adjacency matrix of space mainly measures the relationship between adjacent space units, and generally uses Queen links (Tu et al., 2023). The spatial effect between adjacent provinces is explored through spatial adjacency matrix analysis. The formula is as follows:

$$W_{0-1} = \begin{cases} 1, i \text{ and } j \text{ are adjacent} \\ 0, \text{ others} \end{cases} \quad (2)$$

Among them, 1 represents that province i and province j are adjacent, and 0 represents that province i and province j are not adjacent.

(3) Spatial economic distance matrix

The spatial economic distance matrix is mainly used to measure the similarity of economic structure and economic development degree among different provinces, and the economic proximity index is measured by the per capita GDP of each province (Li et al., 2022). Through the analysis of spatial economic distance matrix, this paper explores whether the similarity of economic structure and economic development degree will affect the impact of digital economy on regional innovation at the spatial level. The formula is as follows:

$$W_{eco} = \frac{1}{\left|GDP_i - GDP_j\right|} \quad (3)$$

GDP_i and GDP represent the per capita provincial GDP of province i and province j, respectively. The larger the W_{eco} the higher the degree of economic proximity between the two provinces.

(4) Space technology matrix

The spatial technology matrix is mainly used to measure the similarity of technology development between different provinces. According to the technology similarity index proposed by Jaffe (1986) and the international patent classification standard, the patent types are divided into A, B, C, D, E, F, G, H and other 8 types for measurement. Through spatial technology matrix analysis, this paper explores whether the similarity of technology development will affect the impact of digital economy on regional innovation at the spatial level. The formula is as follows:

$$W_{tec} = \frac{\sum_{k=1}^{K} T_{ik} T_{jk}}{\sqrt{\sum_{k=1}^{K} T_{ik}^2 \sum_{k=1}^{K} T_{jk}^2}} \quad (4)$$

Where, T_{ik} and T_{jk} denotes the total number of authorizations of class k ($1 \le k \le 8$) patents in province i and province j, respectively, in a certain time period. The value of W_{tec} is between 0 and 1, and the greater the value, the higher the degree of technical proximity between the two provinces.

3.1.4 Control Variables

GDP per capita, foreign direct investment and R&D investment are selected as control variables (see Table 3).

(1) GDP per capita (yuan) (PCGDP), usually using the sum of the province's GDP divided by the province's resident population, commonly used to measure the level of economic development of a province, with reference to the practice of Li Linhan and other scholars, using it to evaluate the economic basis of the province's innovation ability.

(2) Foreign direct investment (million dollars) (FDI), usually the cumulative number of contract utilization of foreign capital, refers to foreign enterprises and economic organizations or individuals (including Hong Kong, Macao and Taiwan compatriots and China's enterprises registered abroad) in accordance with China's relevant policies and regulations, the use of cash, physical, technical and other foreign-owned enterprises in our province, and with the province's domestic enterprises or economic organizations jointly held Sino-foreign joint ventures.

Table 3: Definition of Control Variables

Variable Name	Sign	Definition
GDP Per Capita (yuan)	PCGDP	The total GDP of the province/the resident population of the province
Foreign Direct Investment (millions of US dollars)	FDI	Development investment by foreign enterprises and economic organizations or individuals within the territory of China
R&D Investment (ten thousand yuan)	R&D	Capital investment in research and experimental development activities

(3) R&D investment (ten thousand yuan) (R&D) refers to the funds allocated by the government, enterprises and other organizations to solve specific scientific and technological problems through entrustment or application reports.

3.2 Data Source

The panel data of 30 provinces in China (excluding Hong Kong, Macao and Taiwan due to the lack of data on Tibet) from 2011 to 2021 are mainly derived from the China Statistical Yearbook China Science and Technology Statistical Yearbook over the years. The descriptive statistics of each variable are shown in Table 4. It can be seen that the standard deviation of the explained variables is large, indicating that there are great differences in regional innovation capabilities among provinces. At the same time, in the control variables, the standard deviation of foreign direct investment and R&D investment is also large, and it is concluded that there are large differences in the input of these two items in each province, which further explains the necessity of this study.

3.3 Empirical Model Selection and Construction

(1) Benchmark regression model construction

In order to explore the impact of digital economy on regional innovation capability, an ordinary panel regression model is first constructed for regression analysis. The model is as follows:

$$ln\mathrm{RIA}_{it} = c + \beta_i ln\mathrm{DE}_{it} + \alpha_i lnControl_{it} + \mu_i + \delta_t + \varepsilon_{it} \quad (5)$$

Among them, RIA_{it} is the regional innovation capability of i province in t years, the explained variable, DE_{it} is the digital economy of i province in t years, the core explanatory variable, Control is a series of control variables (per capita GDP, foreign direct investment, R&D investment), c is the intercept term, β_i and α_i the coefficients of the core explanatory variables and control variables respectively, μ_i is the individual fixed effect, δ_t is the time fixed effect, and ε_{it} is the random error term.

(2) Construction of spatial econometric model

Relevant studies have shown that digital economy and proximity will have an impact on regional innovation capability, and this impact is usually not isolated, but has a significant spatial correlation. At the same time, different spatial factors have different effects on regional innovation. In order to further analyze the internal logical relationship between digital economy, proximity and regional innovation capability, the spatial econometric model is selected for in-depth analysis. Then, on the basis of formula (5), through the spatial weight matrix, it is extended to a spatial econometric model. The spatial model is as follows:

$$ln\mathrm{RIA}_{it} = l + \rho Wln\mathrm{RIA}_{it} + \beta_i ln\mathrm{DE}_{it} + \alpha_i lnControl_{it} + \theta_i Wln\mathrm{DE}_{it} + \gamma_i WlnControl_{it} + \mu_i + \delta_t + \varepsilon_{it} \quad (6)$$

W is the spatial weight matrix, ρ is the spatial autoregressive coefficient of the explained variable, β_i is the explanatory variable coefficient, α_i is the control variable coefficient, θ_i is the spatial interaction term coefficient of the explanatory variable, γ_i is the spatial interaction term coefficient of the control variable, l is the constant term, μ_i is the individual fixed effect, δ_t is the time fixed effect, ε_{it} is the random error term.

(3) Construction of regulatory model

Science is the source of technology and technology is the source of industry. Based on the relevant theories of regional innovation system, along the basic paradigm of scientific and technological innovation, collaborative innovation is used as an intermediary variable, that is, the synergy between science, technology and industry. The three indicators of basic research, applied research and experimental development investment are used to measure the degree of standardization of regional innovation paradigms. In summary, in order to further test whether collaborative innovation will improve the impact of digital economy and proximity on regional innovation capabilities, a adjustment model will be constructed based on the spatial econometric model. The adjustment model is as follows:

$$ln\mathrm{RIA}_{it} = l + \rho Wln\mathrm{RIA}_{it} + \beta_0 ln\mathrm{DE}_{it} + \theta_0 Wln\mathrm{DE}_{it} + \beta_1 ln\mathrm{DE}_{it} {*} ln\mathrm{CI} + \theta_1 Wln\mathrm{DE}_{it} {*} ln\mathrm{CI} + \mu_i + \delta_t + \varepsilon_{it} \quad (7)$$

W is the spatial weight matrix, ρ is the spatial autoregressive coefficient of the explained variable, θ_0 is the spatial spillover coefficient of the core explanatory variable, θ_1 is the spatial spillover coefficient of the cross term, β_0 is the estimation coefficient of the core explanatory variable, β_1 is the estimation coefficient of the cross term, l the constant term, μ_i the individual fixed effect, δ_t is the time fixed effect, and ε_{it} is the random error term.

4. EMPIRICAL RESULTS AND ANALYSIS

4.1 Benchmark Regression

In order to eliminate the error caused by the collinear of variables, the multicollinearity test is carried out to improve the accuracy of the model. Using stata17.0 software to calculate (see Table 5), the VIF value is less than 10, indicating that there is no serious collinearity problem in each variable; secondly, in the choice of measurement methods, after the Hausman test (Prob>chi2=0.0000), the hypothesis of better random effects is rejected, and the double fixed effect model is selected. In Table 6, Model (1) is the result of not introducing explanatory variables, and Model (2) is the result of introducing explanatory variables.

It can be seen from Table 6 that the digital economy, foreign direct investment, and R&D investment are positive at the significant levels of 5%, 1%, and 1%, respectively, indicating that the indicator has a positive effect on regional innovation capabilities, while the per capita GDP is not significant, indicating that the indicator has a direct impact on regional innovation capabilities. Combined with the regression coefficient, it is found that under the condition that other variables remain unchanged, for every 1 unit increase in the digital economy, the regional innovation capacity can increase by 0.196 units; for every 1 unit increase in foreign direct investment, the regional innovation capacity can increase by 0.187 units; for every 1 unit increase in R&D investment, the regional innovation capability can increase by 0.698 units. Through further comparison, it is found that R&D investment has the most significant effect on the improvement of regional innovation ability. The main reason may be that the two main problems faced by China's innovation are capital constraints and low efficiency, and the investment of R&D funds can quickly resolve the problem of capital level, and then effectively improve the innovation ability. Secondly, the development of the digital economy has a greater impact on regional innovation capabilities. With the advent of the digital economy era, the industrial structure has been

Table 4: Descriptive Statistics of Data

Variable	N	Mean Value	Standard Deviation	Minimum Value	Maximum Value
RIA	330	-3.098	1.388	-6.896	-0.518
DE	330	-2.826	0.678	-4.553	-0.340
PCGDP	330	10.791	0.439	9.682	12.009
FDI	330	11.281	1.401	7.948	14.825
R&D	330	14.322	1.353	10.964	17.034

Note: All variables take natural logarithm.

Table 5: Collinearity Test Results

Variables	VIF
DE	2.929
PCGDP	3.085
FDI	5.372
R&D	3.455

Table 6: Benchmark Regression Results

Variables	(1) RIA	(2) RIA
lnDE	-	0.196**
		(2.54)
lnPCGDP	0.159	0.041
	(1.39)	(0.33)
lnFDI	0.206***	0.187***
	(4.08)	(3.69)
lnR&D	0.729***	0.698***
	(17.89)	(16.60)
Cons_	-17.573	-15.099***
	(-17.57)	(-10.85)
Time Fixed	YES	YES
Regional Fixed	YES	YES
R^2	0.8533	0.8564
adj R^2	0.8518	0.8545
N	330	330

Note: *, * *, * * * are significant at 10 %, 5 % and 1 %, respectively.

Table 7: Moran's I of Regional Innovation Capability 2011-2021

Year	Inverse-Istance Weights Matrix			Spatial Adjacent Matrix		
	Moran's I	Z (I)	P (I)	Moran's I	Z (I)	P (I)
	0.049	2.444	0.007	0.213	2.348	0.009
	0.04	2.167	0.015	0.178	2.003	0.023
	0.028	1.798	0.036	0.130	1.534	0.063
	0.028	1.788	0.037	0.124	1.478	0.07
	0.026	1.748	0.04	0.121	1.45	0.074
	0.026	1.742	0.041	0.117	1.42	0.078
	0.016	1.46	0.072	0.086	1.136	0.128
	0.013	1.367	0.086	0.073	1.01	0.156
	0.009	1.25	0.106	0.054	0.826	0.204
	0.01	1.276	0.101	0.064	0.922	0.178
	0.008	1.243	0.103	0.068	0.901	0.163
Year	**Spatial Economic Distance Matrix**			**Space Technology Matrix**		
	Moran's I	Z（I）	P（I）	Moran's I	Z（I）	P（I）
	0.128	1.44	0.075	-0.028	4.900	0.000
	0.148	1.603	0.054	-0.028	5.441	0.000
	0.153	1.627	0.052	-0.026	6.600	0.000
	0.153	1.627	0.052	-0.026	6.987	0.000
	0.157	1.658	0.049	-0.026	7.108	0.000
	0.169	1.776	0.038	-0.025	7.425	0.000
	0.155	1.67	0.047	-0.025	7.670	0.000
	0.156	1.666	0.048	-0.025	7.873	0.000
	0.135	1.479	0.070	-0.024	8.028	0.000
	0.126	1.391	0.082	-0.025	7.332	0.000

continuously transformed and upgraded, thereby further promoting the improvement of innovation capabilities (Ruibo et al., 2021), H1 was confirmed. Since the results of OLS regression do not consider spatial factors, the spatial econometric model is further used for analysis.

4.2 Spatial autocorrelation Test

4.2.1 Global Moran's Index

Before carrying out spatial econometric regression, first of all, it is necessary to carry out spatial autocorrelation analysis on the regional innovation ability of each province, that is, to measure the Moran index of regional innovation ability, and to use the global Moran index (Moran's I) to test the spatial correlation. The calculation formula is:

$$Moran's\ I=\sum_{i=1}^{n}\sum_{j=1}^{n}W_{ij}\left(Y_i-\bar{Y}\right)\left(Y_j-\bar{Y}\right)\quad S^2\sum_{i=1}^{n}\sum_{j=1}^{n}W_{ij} \tag{8}$$

In the formula, $S^2=\frac{1}{n}\sum_{i=1}^{n}(Y_i-\bar{Y})$, $\bar{Y}=\frac{1}{n}\sum_{i=1}^{n}Y_i$, n are the 30 provinces and autonomous regions of this study, Y_i representing the regional innovation ability of each province and city, $\bar{Y}$ indicating the mean value of the corresponding index, W_{ij} is the spatial weight matrix. The value range of Moran's index is $[-1,1]$, if Moran's index > 0, it means that the inter-provincial observed variables show a positive spatial correlation; if Moran's index<0, it indicates that the inter-provincial observation variables are spatially negatively correlated; if Moran's index=0, it means that there is no spatial correlation between the observed variables.

The Moran index of regional innovation capability of each province from 2011 to 2021 is calculated by stata17.0 software (see Table 7). It can be seen that most of the Moran's index passed the 10% significance test and was not zero during the observation period (2011-2021), indicating that the global Moran's index of regional innovation capability had significant spatial autocorrelation, which further explained the rationality of selecting the spatial econometric model. Among them, in the inverse distance weight matrix and the spatial adjacency matrix, it can be seen that with the change of time, the spatial positive correlation is gradually disappearing, that is, the global Moran index significance of regional innovation capability is weakening. After 2019, none of them passed the significance test. From the change of P value, it is not difficult to find that the weakening degree of geographical distance is less than that of geographical adjacency, that is, the influence of geographical distance on regional innovation ability is stronger than that of geographical adjacency. In the spatial economic distance matrix and spatial technology matrix, the spatial correlation of regional innovation ability is still significant.

4.2.2 Moran Scatter Plot

The Moran's I index scatter plot has four spatial connection types. The first type is located in the first quadrant (H-H), and the H-H type shows a spatial positive correlation, that is, the agglomeration of high-level provinces and high-level provinces; the second category is located in the second quadrant (L-H), and the L-H type shows a spatial negative correlation, that is, the agglomeration of low-level provinces and high-level provinces; the third category is located in the third quadrant (L-L), and the L-L type shows a positive spatial correlation, that is, the agglomeration of low-level provinces and low-level provinces; the fourth category is located in the fourth quadrant (H-L), and the H-L type shows a spatial negative correlation, that is, the agglomeration of high-level provinces and low-level provinces. The Moran scatter plot of

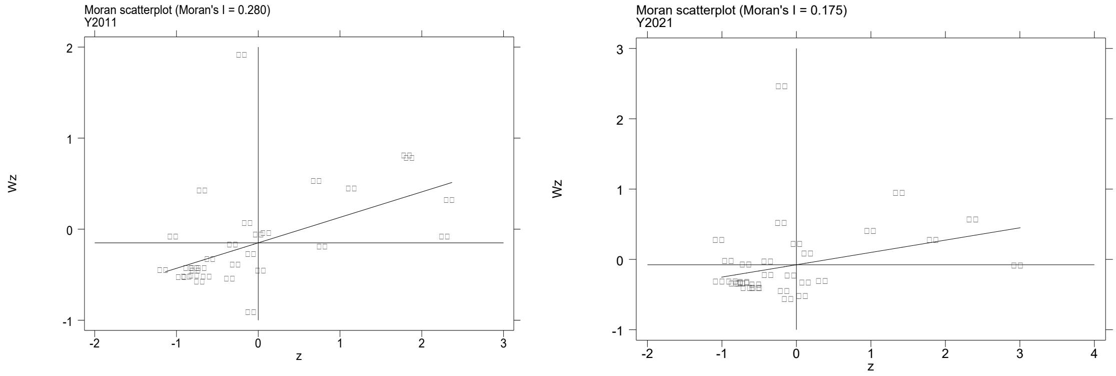

Figure 2: Moran's I Index Scatter Diagram of Regional Innovation Capability in 2011 and 2021

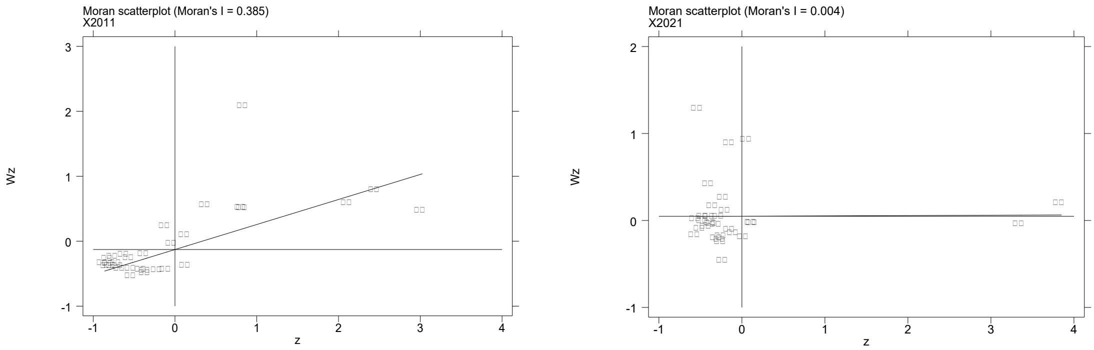

Figure 3: Moran's I Index Scatter Plot of Digital Economy in 2011 and 2021

regional innovation capability and digital economy of each province in 2011 and 2021 was made by stata17.0 software (see Figures 2 and 3).

It can be seen from Figure 2 and 3 that the scatter points of most provinces are distributed in the first quadrant and the third quadrant, which indicates that there is a positive spatial correlation, which again confirms the rationality of using the spatial econometric model to analyze the spatial effect of the selected variables. From the perspective of regional location, provinces with lower regional innovation ability are more adjacent to other provinces with lower regional innovation ability, and provinces with lower digital economy level are more adjacent to other provinces with lower digital economy level, and vice versa. In addition, the regions represented by Beijing-Tianjin-Hebei, Yangtze River Delta and Pearl River Delta show high-high spatial agglomeration characteristics in regional innovation, showing strong regional innovation ability. The provinces also show obvious regional differences in the level of digital economic development, and the high-high agglomeration and low-low agglomeration effects are obvious.

4.2.3 Selection of Spatial Model

Before estimating the model, we first need to combine the Lagrange multiplier (LM) and the robust Lagrange multiplier (Robust LM) to test, and determine whether the spatial correlation exists in the error term or in the lag term to determine which of the three models of the spatial error model (SEM), the spatial lag model (SAR), and the spatial Durbin model (SDM) is used. Secondly, it is necessary to judge whether the spatial Durbin model (SDM) will degenerate into the spatial error model (SEM) and the spatial lag model (SAR) through Wald and likelihood ratio (LR). The specific test results are shown in Table 8.

The inverse distance weight matrix and the spatial technology matrix have passed the Wald and LR significance test, indicating that the spatial Durbin model will not degenerate into the spatial error model and the spatial lag model, so the spatial Durbin model is used to present the data analysis conclusion. The spatial adjacency matrix passes the LM and Robust LM tests, and the spatial Durbin model is determined to be used, and the LR test is passed, but the Wald test is not passed, indicating that the spatial Durbin model may be simplified. The spatial economic distance matrix passed the LM and Robust LM tests, and the spatial Durbin model was determined to be used and passed the LR test. However, the Wald-spatial lag did not pass the significance test, indicating that the spatial Durbin model may be simplified into a spatial lag model. In order to make the results of the article more reasonable and convincing, the spatial Durbin model is still used to present the results. At the same time, the spatial lag model and the spatial error model are presented together to present the results of data analysis for comparison.

According to the statistics of Hausman test, the fixed effect model is selected. Through the LR test results (see Table 9), the double fixed effect is better than the individual fixed effect, and the time fixed effect is better than the double fixed effect. Therefore, the time fixed effect model is selected. In summary, the spatial Dubin model with fixed time is finally used.

4.2.4 Spatial Durbin Model Measurement Results

(1) Overall regression results

The spatial lag model, spatial error model and spatial Durbin model are used to analyze the spatial impact of digital economy on regional innovation capability (see Table 10 and Table 11). Based on the spatial Durbin model, supplemented by the spatial lag model and the spatial error model, combined with the four types of matrices, the direct effect (Main) and the spatial spillover effect (Wx) are analyzed.

It can be seen from Table 10 that in the inverse distance weight matrix, the spatial autoregressive coefficient rho of the spatial Durbin model is significantly positive at the 5% level (0.270). The coefficient of the Main effect column of the digital economy is negative and not significant, which may reflect the combined effects of various factors, including the time lag effect of digital transformation, measurement bias, or the innovation effect of the digital economy is mainly achieved through

Table 8: Diagnostic Test Results of Spatial Measurement

Test Method	t	P	Test Method	t	P
Inverse-Istance Weights Matrix					
Moran's I	25.974	0.000	Hausman	20.930	0.001
LM-Spatial Lag	544.336	0.000	LR-Spatial Lag	41.860	0.000
Robust LM-Spatial Lag	448.362	0.000	Wald-Spatial Lag	9.130	0.0579
LM-Spatial Error	103.619	0.000	LR-Spatial Error	43.390	0.000
Robust LM-Spatial Error	7.645	0.000	Wald-Spatial Error	12.470	0.0142
Spatial Adjacent Matrix					
Test Method	t	P	Test Method	t	P
Moran's I	15.990	0.000	Hausman	24.030	0.000
LM-Spatial Lag	239.111	0.000	LR-Spatial Lag	52.070	0.000
Robust LM-Spatial Lag	107.769	0.000	Wald-Spatial Lag	3.680	0.452
LM-Spatial Error	140.227	0.000	LR-Spatial Error	62.270	0.000
Robust LM-Spatial Error	8.885	0.003	Wald-Spatial Error	7.200	0.126
Spatial Economic Distance Matrix					
Test Method	t	P	Test Method	t	P
Moran's I	8.803	0.000	Hausman	27.760	0.000
LM-Spatial Lag	72.150	0.000	LR-Spatial Lag	47.990	0.000
Robust LM-Spatial Lag	41.164	0.000	Wald-Spatial Lag	2.270	0.6862
LM-Spatial Error	37.425	0.000	LR-Spatial Error	33.220	0.000
Robust LM-Spatial Error	6.439	0.011	Wald-Spatial Error	7.840	0.098
Space Technology Matrix					
Test Method	t	P	Test Method	t	P
Moran's I	28.176	0.000	Hausman	24.330	0.000
LM-Spatial Lag	557.142	0.000	LR-Spatial Lag	168.020	0.000
Robust LM-Spatial Lag	508.953	0.000	Wald-Spatial Lag	14.900	0.005
LM-Spatial Error	52.368	0.000	LR-Spatial Error	151.760	0.000
Robust LM-Spatial Error	4.179	0.041	Wald-Spatial Error	19.370	0.001

spatial spillover rather than local direct effects. The spatial interaction term coefficient in the Wx column is positively significant. In the spatial adjacency matrix, the spatial autoregressive coefficient rho of the spatial Durbin model is significantly positive at the 5% level (0.168); the spatial interaction coefficient of the digital economy in the Main effect column and the Wx column is not significant. Among them, rho coefficient reflects the spatial correlation degree of innovation ability in adjacent areas, Main effect column coefficient indicates the direct impact of digital economy on local innovation ability, and Wx column coefficient measures the spillover effect of local digital economy development on innovation ability in adjacent areas. H2a is supported by data, and H2b is not supported by data.

From Table 11, we can see that in the spatial economic distance matrix, the spatial autoregressive coefficient rho of the spatial Durbin model is

Table 9: Fixed Model Selection Results

Inverse-Istance Weights Matrix			Spatial Adjacent Matrix		
Ind Contrast Both	t	P	Ind Contrast Both	t	P
	16.380	1.000		23.260	1.000
Time Contrast Both	t	P	Time Contrast Both	t	P
	763.890	0.000		755.140	0.000
Spatial Economic Distance Matrix			Space Technology Matrix		
Ind Contrast Both	t	P	Ind Contrast Both	t	P
	27.260	1.000		49.240	1.000
Time Contrast Both	t	P	Time Contrast Both	t	P
	764.300	0.000		783.230	0.000

significantly positive at the 1% level (0.358); the coefficient of digital economy in the Main effect column is positive and significant, and the coefficient of spatial interaction term in the Wx column is negative and significant. This negative spillover effect reflects the phenomenon of "digital divide" between regions with similar economic development levels, that is, the developed areas of digital economy have siphon effect of innovative elements on regions with similar economic structure but low degree of digitization. In the spatial technology matrix, the spatial autoregressive coefficient rho of the spatial Durbin model is significantly negative at the 1% level (−7.399). This phenomenon reflects the competition effect between regions with similar technologies, and further indicates that provinces with similar technological structures show a "trade-off" competition pattern in regional innovation capabilities. That is, when a province has a strong innovation capability, the innovation performance of its technologically adjacent provinces is often relatively weak, which is mainly due to the direct competition in high-end talents, R&D funds, market share and other innovation factors in regions with similar technologies. The "siphon effect" of strong regions weakens the innovation ability of regions with close technology but weak strength. The coefficient of the digital economy in the Main effect column is positive and significant, and the coefficient of the spatial interaction term in the Wx column is positive and significant. H2c and H2d are supported by data.

(2) Spatial effect decomposition

The above has preliminarily verified the spatial effect of the impact of digital economy on regional innovation capability through the regression results of the spatial Durbin model. In order to more intuitively clarify the impact of digital economy and control variables on regional innovation capability, the partial differential method of LeSage & Pace (2009) will be used to decompose the total effect of the spatial Durbin model into direct effect (local effect) and indirect effect (spillover effect) (see Table 12). The direct effect measures the impact of the development of digital economy in the region on the innovation ability of the local region. The indirect effect reflects the impact of the development of digital economy in the region on the innovation ability of other regions through spatial spillover. The total effect is the sum of direct effect and indirect effect, which measures the comprehensive impact of the change of digital economy in the region on the innovation ability of the whole spatial system.

The spatial effect of the digital economy presents a significant "proximity dependence" feature. In the inverse distance weight matrix, the direct effect of the digital economy is not significant, but the indirect effect is significantly positive, which indicates that the development of the digital economy has a significant positive spillover on the provinces with close geographical distance, reflecting the "near water platform first month" effect. In the spatial economic distance matrix, the direct effect of digital economy is significantly positive, and the indirect effect is significantly negative, which reflects the "digital divide" and "siphon

Table 10: Spatial Durbin Model Regression Results

Variables	Inverse-Istance Weights Matrix			Spatial Adjacent Matrix		
	SAR	SEM	SDM	SAR	SEM	SDM
			Main			
lnDE	-0.048	-0.033	-0.034	-0.029	-0.019	-0.020
	(-1.15)	(-0.77)	(-0.78)	(-0.70)	(-0.46)	(-0.47)
lnPCGDP	0.599***	1.038***	0.809***	0.778***	1.038***	0.829***
	(4.13)	(7.55)	(3.61)	(5.82)	(8.00)	(3.71)
lnFDI	0.233***	0.250***	0.225***	0.251***	0.260***	0.237***
	(8.08)	(8.44)	(7.66)	(8.84)	(8.86)	(8.20)
lnR&D	-0.250***	-0.292***	-0.250***	-0.292***	-0.312***	-0.283***
	(-4.46)	(-5.06)	(-4.29)	(-5.28)	(-5.46)	(-4.98)
			Wx			
lnDE			0.355**			0.072
			(2.38)			(0.81)
lnPCGDP			-0.570			-0.432
			(-1.57)			(-1.48)
lnFDI			0.172			0.169**
			(1.55)			(2.51)
lnR&D			-0.448*			-0.028
			(-1.79)			(-0.28)
Rho	0.413***		0.270**	0.244***		0.168**
	(5.07)		(1.96)	(4.20)		(2.33)
Lambda		0.466 ***			0.223***	
		(4.13)			(3.14)	
Sigma2_e	0.020***	0.021***	0.020***	0.021***	0.021***	0.020***
	(12.22)	(12.18)	(12.23)	(12.20)	(12.19)	(12.21)
N	330	330	330	330	330	330
R-Squared	0.1160	0.1557	0.094	0.1232	0.1436	0.1346

Note: *, * *, * * * are significant at 10 %, 5 % and 1 %, respectively.

effect" between regions with similar economic development levels. In the spatial technology matrix, the direct and indirect effects of the digital economy are significantly positive, indicating that regions related to the technology field can achieve synergistic promotion through the development of the digital economy.

In the change of traditional proximity effect, the results of spatial adjacency matrix show that the direct effect and indirect effect of digital economy are not significant, which further confirms the weakening trend of geographical adjacency effect, which is consistent with the time change trend of global Moran's index. In contrast, economic proximity and technological proximity still play an important role, indicating that in the era of digital economy, proximity based on functional connections is replacing proximity based on geographical locations.

The foreign direct investment in the control variables shows significant positive direct and indirect effects in the four matrices, which reflects its dual role in promoting regional innovation capabilities. The effect of R&D investment varies with the type of proximity, showing a negative effect in the geographical dimension, and a positive direct effect but a negative indirect effect in the economic and technical dimensions.

4.2.5 Regulatory Effect Analysis

In order to further explore the moderating effect of collaborative innovation on the promotion of regional innovation ability by digital economy, this paper constructs collaborative innovation indicators and introduces a moderating effect model for analysis. Collaborative innovation can reflect the organic connection between the various links of the innovation value chain. The innovation process has obvious systematic and cumulative characteristics. The scientific knowledge generated by basic research needs to be transformed into technical solutions through applied research, and then through experimental development to achieve industrial application. When the proportion of the three inputs is unbalanced, there will be a fracture of the innovation chain. Therefore, the degree of coordination and unity among the three directly determines the realization path of knowledge spillover effect and the transformation level of innovation efficiency. Further, considering the important impact of the digital economy on the innovation capability of the region and neighboring regions, by adding the moderating variable of collaborative innovation on the basis of the spatial Durbin model, the entropy weight method is used to synthesize the indicators of each dimension of collaborative innovation (see Table 13), and the moderating effect model constructed by Equation (3) is used to test whether collaborative innovation can optimize the innovation promotion effect of the digital economy (see Table 14).

The moderating effect analysis reveals the important influence of collaborative innovation on the mechanism of digital economy. In the main effect of Main, the coefficient of digital economy is negative but the coefficient of collaborative innovation cross term (lnDE*lnCI) is increasing, which indicates that collaborative innovation can alleviate the "structural mismatch" problem of digital economy, that is, when the coordination of each link of the innovation system is low, the digital

Table 11: Spatial Durbin Model Regression Results

Variables	Spatial Economic Distance Matrix			Space Technology Matrix		
	SAR	SEM	SDM	SAR	SEM	SDM
			Main			
lnDE	0.477***	0.525***	0.364***	2.596***	0.585***	2.596***
	(5.11)	(6.03)	(4.15)	(3.06)	(6.00)	(3.06)
lnPCGDP	0.247*	0.093	0.017	-2.620	0.201*	-2.620
	(1.77)	(0.78)	(0.09)	(-1.37)	(1.65)	(-1.37)
lnFDI	0.147***	0.144***	0.150***	1.847***	0.167***	1.847***
	(3.02)	(3.14)	(3.24)	(5.32)	(3.28)	(5.32)
lnR&D	0.631***	0.665***	0.632***	-0.696***	0.588***	-0.696***
	(14.74)	(15.91)	(15.97)	(-4.41)	(12.80)	(-4.41)
			Wx			
lnDE			-0.557**			73.083***
			(-2.41)			(3.03)
lnPCGDP			0.991**			-70.343
			(2.25)			(-1.32)
lnFDI			0.372***			50.386***
			(2.72)			(5.13)
lnR&D			-0.807***			-36.753***
			(-6.27)			(-6.94)

Note: *, * *, * * * are significant at 10 %, 5 % and 1 %, respectively.

technology investment often appears the dilemma of "technology without transformation." The improvement of collaborative innovation can open up the complete chain from basic research to industrial application and improve the transformation efficiency of digital economy. The negative main effect reflects the common phenomenon of "digital paradox" in the development of digital economy, that is, a large number of digital inputs fail to be effectively transformed into innovation output, and the moderating effect of collaborative innovation provides a way to solve this paradox. The cross term coefficient measures the adjustment intensity of collaborative innovation to the digital economy effect. It is assumed that H3 is preliminarily confirmed.

In the Wx spatial interaction term, the cross-term coefficient becomes smaller after the adjustment of collaborative innovation, indicating that a perfect local innovation system can reduce the dependence on external spillovers and achieve higher-quality endogenous growth. This finding provides a key inspiration for digital economy policy-making, that is, simple digital infrastructure investment or technology introduction can not bring about the improvement of innovation ability, and it is necessary to simultaneously build a collaborative innovation system covering the whole chain of "research-development-application". All regions should avoid the policy tendency of "emphasizing quantity over quality, emphasizing investment over coordination", and pay more attention to the construction of industry-university-research collaborative platform and the systematic integration of innovation elements. The coefficient of Wx spatial interaction term represents the spillover effect of local digital economy on the innovation ability of neighboring regions, and the adjusted coefficient reflects the influence of collaborative innovation on this spatial spillover effect. It is assumed that H3 is partially verified.

4.2.6 Robustness Test

(1) Eliminate some samples

Because the economic and economic strength and per capita income of municipalities are much higher than those of most provinces, and municipalities have more autonomy in administration and economy, there are differences with ordinary provinces. In order to make the data measurement more accurate and convincing, referring to the practice of Wan et al. (2023), the data of the four municipalities in China are removed, and the data from 2011 to 2021 are continued. Regression analysis (see Table 15), robustness test.

The coefficient size and significance level of the core explanatory variable digital economy are consistent with the regression results of the benchmark in Table 6. In addition, except that the control variable per capita GDP changes greatly, the remaining control variables are floating up and down in a small range, indicating that the above research results are robust, and the R^2 value is large, which can also guarantee the credibility of the model test results from the side.

(2) Replace the spatial weight matrix

In order to test the impact of the spatial weight matrix on the research, the spatial weight matrix is replaced to illustrate the robustness of the empirical results, and the spatial economic geography weight matrix is used for testing (see Table 16). The significance level of the core explanatory variable digital economy is basically consistent with the previous empirical results, indicating that the empirical results of the spatial Durbin model are robust. In addition, the model ρ of the robustness test passes the test, indicating that the test model is better, and the R-squared and Log-likelihood values are larger, which can also guarantee the credibility of the model test results from the side.

5. DISCUSSIONS

Through the spatial econometric analysis of panel data of 30 provinces in China from 2011 to 2021, this paper constructs a theoretical framework of the relationship between digital economy, proximity and regional innovation ability, and verifies the moderating effect of collaborative innovation. This framework provides a new theoretical perspective for understanding the spatial characteristics of regional innovation in the new era by analyzing how the development of digital economy reshapes the traditional proximity mechanism and how collaborative innovation optimizes this process. In the last section, we discuss the implications of the research findings for regional economic theory and digital economic

Table 12: Effect Decomposition Results of Spatial Durbin Model

Variables	Inverse-Istance Weights Matrix			Spatial Adjacent Matrix		
	Direct Effect	Indirect Effect	Total Effect	Direct Effect	Indirect Effect	Total Effect
lnDE	-0.026	0.484**	0.458*	-0.016	0.082	0.066
	(-0.57)	(2.10)	(1.88)	(-0.35)	(0.81)	(0.57)
lnPCGDP	0.795***	-0.439	0.356	0.809***	-0.327	0.481
	(3.71)	(-0.92)	(0.80)	(3.83)	(-1.02)	(1.60)
lnFDI	0.232***	0.309***	0.542***	0.249***	0.240***	0.489***
	(8.38)	(2.78)	(4.94)	(9.19)	(3.53)	(7.01)
lnR&D	-0.260***	-0.743*	-1.003**	-0.286***	-0.095	-0.381***
	(-4.58)	(-1.91)	(-2.55)	(-5.14)	(-0.86)	(-3.16)
Variables	Spatial Economic Distance Matrix			Space Technology Matrix		
	Direct Effect	Indirect Effect	total Effect	Direct Effect	Indirect Effect	Total Effect
lnDE	0.324***	-0.629*	-0.305	0.409**	9.468**	9.877**
	(3.17)	(-1.77)	(-0.73)	(2.33)	(2.17)	(2.18)
lnPCGDP	0.113	1.498**	1.611***	-0.573	-9.321	-9.894
	(0.71)	(2.45)	(2.82)	(-1.54)	(-1.21)	(-1.22)
lnFDI	0.198***	0.632***	0.830***	0.358***	6.452***	6.810***
	(3.86)	(2.99)	(3.41)	(3.94)	(2.96)	(3.02)
lnR&D	0.569***	-0.863***	-0.294	0.588***	-5.459***	-4.870***
	(13.68)	(-4.67)	(-1.42)	(9.58)	(-3.71)	(-3.21)

TNote: *, * *, * * * are significant at 10 %, 5 % and 1 %, respectively.

Table 13: Regional Innovation System Related Indicators

First Grade Indexes	Second Index	Weight
Collaborative Innovation (CI)	Basic research investment	0.382
	Applied research input	0.311
	Test development investment	0.307

policy, and outline the limitations of this paper.

5.1 Contribution to the Theory

This paper has made a number of theoretical contributions to the research on the relationship between digital economy and regional innovation capability. First of all, we reveal how the development of digital economy reconstructs the mechanism of traditional proximity, and provide new empirical evidence for the evolution of proximity theory in the digital age. The traditional proximity theory emphasizes the core role of geographical distance and geographical adjacency in knowledge spillover, but our research shows that with the rapid development of digital technology, this proximity advantage based on physical space is gradually weakening. Through the time series analysis of Moran's index, we found that the spatial autocorrelation of geographical proximity decreased significantly during the observation period, which was consistent with the theoretical expectations of "death from distance" (Schultz, 1998) and "geographical end" (O'Brien,1992). In addition, we find that this weakening does not occur uniformly in all types of proximity, and economic proximity and technological proximity still maintain important influence, which indicates that the proximity theory needs to change from a single geographical dimension to a multi-dimensional proximity framework.

Secondly, our research expands the theoretical cognition of the spatial spillover effect of the digital economy. Different from previous studies, which mainly focus on the direct impact of digital economy on regional innovation capability (Brynjolfsson & McAfee, 2014), we reveal the spatial heterogeneity of the impact of digital economy through the effect decomposition of spatial Durbin model. The study found that the spillover effect of the digital economy shows obvious "proximity dependence" characteristics. It shows positive spillover under the inverse distance weight matrix, negative spillover under the economic distance matrix, and positive again under the technology matrix. This complex spatial effect model shows that the digital economy does not simply promote or inhibit inter-regional innovation cooperation, but has a differentiated impact through different proximity mechanisms. This finding challenges the assumption of "frictionless diffusion" in the digital economy, and further emphasizes the importance of spatial context in the effect of the digital economy (Gertler, 2003).

Thirdly, we innovatively introduce collaborative innovation as a moderating variable, which provides a new theoretical perspective for understanding the mechanism of digital economy (Cooke, 1992; Lundvall, 1992). Based on the theory of regional innovation system, the collaborative innovation index we constructed covers the coordination degree of basic research, applied research and experimental development. This framework transcends the focus of previous research on a single innovation element. The analysis of moderating effect shows that collaborative innovation can significantly improve the impact of digital economy on regional innovation capability, especially under the condition of different spatial proximity, showing a differentiated

Table 14: Estimated Results of Moderating Effect

Inverse-Istance Weights Matrix		Spatial Adjacent Matrix		Spatial Economic Distance Matrix		Spatial Economic Distance Matrix	
Main							
lnDE	-0.200*** (-3.62)	lnDE	-0.125** (-2.13)	lnDE	-0.174*** (-2.92)	lnDE	-0.214*** (-3.75)
lnDE*lnCI	-0.031*** (-3.56)	lnDE*lnCI	-0.033*** (-3.65)	lnDE*lnCI	-0.032*** (-3.59)	lnDE*lnCI	-0.037*** (-4.37)
Wx							
lnDE	0.042* (0.20)	lnDE	0.371*** (3.27)	lnDE	0.149 (1.46)	lnDE	0.387* (1.15)
lnDE*lnCI	-0.033* (-0.83)	lnDE*lnCI	0.019* (0.93)	lnDE*lnCI	0.027* (-1.76)	lnDE*lnCI	0.035* (0.60)
Rho	0.700*** (10.75)	rho	0.470*** (8.19)	rho	0.460*** (7.63)	rho	0.706*** (10.59)
Sigma2_e	0.025*** (12.12)	Sigma2_e	0.028*** (12.01)	Sigma2_e	0.028*** (12.00)	Sigma2_e	0.025*** (12.14)
Observa-tions	330	Observa-tions	330	Observa-tions	330	Observa-tions	330
R-Squared	0.2482	R-Squared	0.3761	R-Squared	0.3513	R-Squared	0.2462

Note: *, * *, * * * are significant at 10 %, 5 % and 1 %, respectively.

Table 15: Benchmark Regression Results

Variables	RIA
lnDE	0.196** (2.33)
lnPCGDP	-0.610*** (-4.03)
lnFDI	0.193*** (4.08)
lnR&D	0.799*** (20.46)
Cons_	-9.510*** (-5.77)
Time Fixed	YES
Regional Fixed	YES
R^2	0.8789
Adj R^2	0.8770
N	286

Note: *, * *, * * * are significant at 10 %, 5 % and 1 %, respectively.

Table 16: Robustness Test Results

Variables	Main	Variables	Wx
lnDE	-0.012 (-0.25)	lnDE	0.299*** (5.04)
Controls	YES		
R-Squared	0.1173		
Log-Likelihood	96.5877		
Rho	0.523*** (9.17)		
N	300		

Note: *, * *, * * * are significant at 10 %, 5 % and 1 %, respectively.

adjustment mode. This finding not only enriches the theoretical connotation of the mechanism of digital economy, but also provides a new analytical framework for understanding the internal coordination mechanism of regional innovation system. In addition, the discovery of this moderating effect shows that the innovation promotion effect of the digital economy does not occur automatically, but needs to be fully released through appropriate innovation system coordination.

5.2 Contributions to Policy and Practice

The policy implications of this paper have important practical significance.

First of all, the research results show that the traditional geographical proximity hypothesis cannot be simply relied on when formulating regional innovation development policies. With the rapid development of the digital economy, policymakers need to re-examine the spatial logic of interregional cooperation, and pay more attention to the similarity of economic structure and the relevance of technical fields, rather than arranging regional cooperation based on geographical location alone (Asheim & Isaksen, 2002). This means that the traditional regional policy framework based on inter-provincial boundaries or geographical plates may need to be adjusted to a more flexible regional coordination mechanism based on functional linkages. For example, in promoting the development of regional integration such as Beijing-Tianjin-Hebei, Yangtze River Delta and Pearl River Delta, more consideration should be given to the economic complementarity and technological correlation between cities, rather than relying solely on geographical proximity advantages.

Secondly, the development policy of digital economy needs to fully consider its spatial heterogeneity effect. Our research shows that the digital economy will have very different spillover effects under different spatial proximity conditions, which requires policymakers to adopt differentiated digital economy development strategies (Chen & Hassink, 2020). For regions with similar levels of economic development, we need to be alert to the “siphon effect” that may be brought about by the development of the digital economy, and avoid the expansion of the digital divide by strengthening interregional coordination mechanisms. For regions related to the technology field, they should actively promote digital economic cooperation and give full play to its positive spillover effects. This precise policy design helps to maximize the innovation promotion effect of the digital economy while avoiding its possible negative spatial effects.

Third, the regulatory role of collaborative innovation provides important guidance for optimizing the construction of regional innovation system. The research findings show that the simple digital economy investment cannot be automatically transformed into the improvement of innovation ability, and its positive effect needs to be amplified through the construction of collaborative innovation mechanism. This requires all regions to pay more attention to the coordinated allocation between basic research, applied research and experimental development while promoting the development of digital economy, so as to avoid the fracture of innovation chain. Specifically, it is necessary to establish a more perfect industry-university-research cooperation mechanism, promote the effective connection between different types of innovation subjects, and ensure that digital technology innovation can be successfully transformed into actual innovation output.

5.3 Limitations

This article also has some limitations.

First of all, due to the limitation of data availability, our analysis time span is from 2011 to 2021.Although this period covers the rapid development stage of China’s digital economy, it may not fully capture the long-term trend of digital economy development. Especially after 2020, the COVID-19 has accelerated the process of digital transformation, which may have a new impact on the relationship between digital economy and proximity, and needs to be further verified in future research.

Secondly, our research is mainly based on provincial panel data, which may mask the heterogeneity characteristics at the city level or enterprise level. The development and innovation activities of the digital economy often have significant urban agglomeration characteristics, and provincial data may not fully reflect this spatial agglomeration effect. Future research can use more detailed spatial scales, such as data at the level of urban agglomerations or metropolitan areas, to further verify our research conclusions.

Third, although the construction of collaborative innovation indicators is based on a mature theoretical framework, there is still a problem of measurement accuracy. The basic research, applied research and experimental development input data we use are mainly from official statistics, which may not fully reflect the complexity and diversity of innovation activities. Especially in the era of digital economy, innovation models are increasingly diversified, and traditional R & D input indicators may need to supplement more indicators reflecting the characteristics of digital innovation.

Finally, this paper focuses on China’s experience, and the international applicability of the research conclusions needs to be further verified. There are significant differences in the development stage, institutional environment and spatial structure of digital economy in different countries. The applicability of our proposed theoretical framework in other countries or regions needs to be verified by comparative research. This also provides an important research direction for future international comparative research.

6. CONCLUSIONS AND SUGGESTIONS

6.1 Conclusions

Based on the panel data of 30 provinces in China from 2011 to 2021, this paper uses spatial Dubin model, spatial effect decomposition and adjustment effect analysis. The main conclusions are as follows:

(1) Digital economy has a significant positive effect on regional innovation capability (Verification H1). The significant positive coefficient of digital economy shows that the development of digital economy can effectively enhance regional innovation ability. Digital infrastructure construction, industrial digital transformation and digital industrialization development provide important support for regional innovation.

(2) Proximity significantly regulates the impact of digital economy on regional innovation capability, and there are significant differences in the mechanism of different types of proximity (verify H2a-H2d). Moran’s index analysis showed that the spatial autocorrelation of geographical proximity decreased significantly during the observation period. The traditional advantages of geographical distance and geographical adjacency are weakening, and geographical adjacency even loses its significant role. The differentiation effect of “local promotion and remote suppression” of economic proximity reflects the problem of “digital divide”; technological proximity has a positive effect in both local and spatial dimensions, and has become the most important type of proximity in the digital age. This finding confirms the mechanism of digital economy development reshaping traditional proximity.

(3) Collaborative innovation can significantly optimize the impact of digital economy on regional innovation capability (Verification H3). Collaborative innovation can effectively alleviate the “structural mismatch” problem of the digital economy and improve the conversion efficiency of digital technology investment by coordinating basic research, applied research and experimental development investment. This shows that the simple input of digital economy cannot be automatically transformed into innovation output, and it is necessary to give full play to the role of digital economy in promoting innovation through a sound collaborative innovation system.

6.2 Policy Recommendations

(1) Constructing regional innovation network based on functional connection.

In view of the fact that the role of geographical proximity is weakened and economic and technological proximity is still important, the traditional regional cooperation model dominated by administrative divisions should be abandoned, and the regional innovation cooperation framework should be redesigned with the industrial chain, innovation chain and value chain as the link. Specifically, relevant departments should identify provinces with similar economic structures and related technical fields, establish cross-regional industrial technology alliances, and promote the development of functional integration. At the same time, in the layout of major national science and technology projects, more consideration should be given to technology correlation rather than geographical location, so as to form an innovation network with “technology-geography” dual embedding.

(2) Implement differentiated digital economy space policy

In view of the significant heterogeneity of the spatial effects of the digital economy, the policy model of “one size fits all” should be avoided. For provinces with similar geographical distances, digital infrastructure interconnection should be strengthened to exert positive spillover effects; for regions with similar levels of economic development, we should be alert to the “digital divide” and “siphon effect”, and avoid homogeneous competition through differentiated technology paths and dislocation development strategies. Relevant departments should establish a regional coordination mechanism for the development of digital economy, and formulate guidelines for division of labor and cooperation in the field of technology, so as to prevent the disorderly flow and repeated allocation of innovation resources.

(3) Crack the “digital paradox” and strengthen the construction of collaborative innovation system.

In view of the "digital paradox" that digital input has not been effectively transformed into innovation output, the construction of collaborative innovation system should be taken as the core of digital economic policy, that is, it is suggested that all regions should establish a full-chain collaborative mechanism covering basic research, applied research and experimental development, so as to avoid the policy bias of "focusing on input rather than transformation, focusing on quantity rather than quality." Specifically, relevant departments should establish an innovation platform for the deep integration of industry, university and research, improve the incentive mechanism for the transformation of scientific and technological achievements, and build a "seamless docking" system from the laboratory to the market. At the same time, collaborative innovation indicators should be included in the assessment system of digital economy development.

(4) Optimize the allocation of innovation factors to avoid regional innovation imbalance.

Based on the discovery of competitive effects in regions with similar technologies, a national-level overall allocation mechanism for innovation factors should be established, and high-end innovation factors should be guided to moderately tilt to regions with better technological foundations in the central and western regions through means such as tax incentives and talent flow policies, so as to avoid excessive concentration of innovation factors in the eastern region. At the same time, relevant departments should also encourage technology-leading regions to promote the coordinated development of regions with similar technology but weak strength through technology export and talent exchange, so as to further form a benign interaction pattern of "cooperation in competition and competition in cooperation."

6.3 Future Research Prospects

With the accelerated iteration of digital technology and the vigorous development of digital economy, regional innovation capability will accelerate the evolution from a single subject to multiple subjects, from single to collaborative innovation, and from local closure to open interaction (Fan et al., 2020). Only by further improving the collaborative innovation mechanism, deepening the innovation benefit sharing mechanism, and accelerating the formation of a new pattern of innovative division of labor with dislocation development and mutual benefit and win-win results can we truly cultivate the fertile soil for innovation in the development of digital economy and promote regional innovation and regional development. In the future, how to build a differentiated regional innovation system to formulate a more complete regional innovation policy, explore the differentiated independent innovation development strategy of different regions, and avoid the "pepper" innovation policy support method is the focus of the next research. In addition, if the unified standard of digital economy measurement is established and improved, it is also the future exploration direction to promote the unified market construction of data-based innovation elements (Runge et al., 2022).

ACKNOWLEDGMENTS

This work was supported by National Social Science Fund Education General Project "Research on the Path of Improving the Efficiency of Scientific and Technological Achievements Transformation in Western Universities" (No.BIA250147), Major Program of Anhui University Scientific Research Project in China (No.2023AH040053), and Action Program for Young-Middle aged Teachers Training in Anhui Province of China (No. JWFX2024010).

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