

## Research Article

# Spatial Association and Explanation of China's Digital Financial Inclusion Development Based on the Network Analysis Method

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As an essential direction for developing inclusive finance, digital financial inclusion breaks through the time and space constraints of inclusive finance development and has extensive connections between different regions. However, no research has modelled the network connections and the role and position of different digital financial inclusion development regions. This study constructed the spatial association network of China's digital financial inclusion development and used the network analysis method and the quadratic assignment procedure (QAP) method to study the structural and locational properties and the influencing factors of the network. We found that (1) although the network had a relatively low density, its connectivity and stability were excellent, and the network structure is not hierarchical; (2) the centrality of some rapidly developing central and western provinces was greater than that of some developed eastern provinces; (3) developed eastern provinces played a net spillover role, driving the development of digital financial inclusion in central and western provinces; and (4) the spatial association was affected by the development level of the PC Internet and economy, the industrial structure, and the spatial adjacency. This study enriches the research on digital financial inclusion and provides a scientific basis for the formulation and implementation of policies to promote the further development of digital financial inclusion.

## 1. Introduction

With the recent rapid development of information technologies, the integration of digital technology and inclusive finance has continued to deepen [1, 2], further improving the accessibility and affordability of inclusive financial services and expanding its coverage [3]. Accordingly, digital financial inclusion is gradually becoming an essential direction for financial inclusion [4]. Depending on digital technology, digital financial inclusion gradually eliminates the time and space constraints for developing inclusive finance, making it possible to provide round-the-clock and full coverage financial services to any corner of the world. This trend requires a holistic approach to explore the development of digital financial inclusion. Unlike the methods used in the existing literature, we adopt a comprehensive approach to construct and analyze the network of digital financial inclusion development in this study.

Similar to financial inclusion [5], existing research on digital financial inclusion mainly focuses on its effect on economic development [6–10], poverty reduction [11–13], and financial stability [14, 15]. These studies only focus on the impact of digital financial inclusion and do not consider the possibility of connections of digital financial inclusion development between regions. This is very important because the development of inclusive finance has apparent spatial spillover effects [16], which are even more pronounced in the development of digital financial inclusion that incorporates digital technology. Guo et al. [17] studied the development of digital financial inclusion among cities in China. They found that the development of digital financial inclusion among cities has a significant positive spatial autocorrelation, that is, a significant positive spatial spillover effect. Furthermore, this effect shows an increasing trend year by year. Similarly, Shen et al. [18] took 101 countries as the research objects and found that countries

with a higher level of digital financial inclusion will influence the development of digital financial inclusion in neighboring countries through spillover effects.

Existing evidence shows that the development of digital financial inclusion is widely connected in different regions. Therefore, it should be regarded as a digital service network that provides around-the-clock and full coverage financial services when studying it. However, to the best of our knowledge, no research explicitly models the network connections and the role and position of different digital financial inclusion development regions. Therefore, this study takes China, the world's largest digital financial inclusion market [19], as the research object and attempts to fill this gap by constructing a spatial association network of digital financial inclusion development. Meanwhile, we use the network analysis method and the quadratic assignment procedure (QAP) method to study the structural and locational properties and the influencing factors of the network in order to identify the spatial characteristics and the critical influencing factors of the development of digital financial inclusion. All findings provide an essential scientific basis for the formulation and implementation of policies for further developing digital financial inclusion, which is vital to realize the sustainable development of inclusive finance.

## 2. Methods and Data

### 2.1. Construction of the Spatial Association Network.

China's spatial association network for the development of digital financial inclusion comprises relationships of digital financial inclusion development between provinces. In the network, the nodes are provinces, and the edges are relationships. The key to constructing a spatial association network is to depict the spatial associations between provinces. According to the research of Mantegna [20], we define a spatial metric through the function of the correlation coefficient and then use this spatial metric (Euclidean distance in this study) as a distance to construct these relationships. The appropriate function is

$$D_{ij} = \sqrt{2(1 - C_{ij})}, \quad (1)$$

where  $i, j = 1, 2, \dots, N$  represents any two different provinces in the 31 provinces (municipalities and autonomous regions collectively referred to as "provinces," excluding Hong Kong, Macao, and Taiwan);  $D_{ij}$  is the Euclidean distance between province  $i$  and  $j$ ;  $C_{ij}$  is the correlation coefficient between two vectors, concretely given by the following formula:

$$C_{ij} = \frac{\sum_{t=1}^T (x_{it} - \bar{x}_i)(x_{jt} - \bar{x}_j)}{\sqrt{\sum_{t=1}^T (x_{it} - \bar{x}_i)^2 \sum_{t=1}^T (x_{jt} - \bar{x}_j)^2}}, \quad (2)$$

where  $x_{it} = (x_{i1}, x_{i2}, \dots, x_{it}, \dots, x_{iT})$  and  $x_{jt} = (x_{j1}, x_{j2}, \dots, x_{jt}, \dots, x_{jT})$ , respectively, denote China's digital financial inclusion index of provinces  $i$  and  $j$  from  $t = 1$  to  $t = T$ .

Motivated by the research of Yang and Liu [21], we can acquire the spatial association matrix between provinces

according to equation (3) after obtaining the Euclidean distance matrix.

$$Q(i, j) = \begin{cases} 1, & Q_{ij} \geq \frac{1}{N} \sum_{j=1}^N Q_{ij}, \\ 0, & Q_{ij} < \frac{1}{N} \sum_{j=1}^N Q_{ij}, \end{cases} \quad (3)$$

where  $Q(i, j)$  represents the spatial association between provinces  $i$  and  $j$ ;  $Q_{ij}$  represents the reciprocal of  $D_{ij}$ ; and the spatial association matrix  $Q(i, j)$  equals to  $(Q_{ij})_{N \times N}$ . Considering that the calculated spatial association matrix is asymmetric, the spatial association network of the digital financial inclusion development we constructed is directional. In addition, compared with traditional network construction methods, our approach eliminates the disadvantage in which the gravity model and the VAR Granger causality model are susceptible to multiple factors [21].

### 2.2. Characterization of the Spatial Association Network

**2.2.1. Whole Network.** In this study, we take four indicators, that is, network density, network connectedness, network hierarchy, and network efficiency, to measure the structural characteristics of the whole network of digital financial inclusion development [22].

Network density is an indicator that reflects the inter-connectedness of the provinces in the network [23]. It can be defined as the ratio of actual relationships to the total possible relationships, and its calculation formula is as follows:

$$\text{density} = \frac{L}{N \times (N - 1)}, \quad (4)$$

where  $L$  denotes the actual number of relationships;  $N$  represents the network's size.

Network connectedness is used to measure the reachability between provinces in the network. If some provinces are not accessible to each other, then the network's connectedness must be small, whereas if the provinces can be directly and indirectly accessible to each other, the network's connectedness must be large. Therefore, network connectedness can be calculated as follows:

$$\text{connectedness} = 1 - \frac{2V}{N \times (N - 1)}, \quad (5)$$

where  $V$  represents the number of unreachable node pairs in the network;  $N$  represents the network's size.

Network hierarchy can measure the extent to which each province in the network is asymmetrically connected to the other, thereby reflecting the hierarchical status of each province. Specifically, its calculation formula is as follows:

$$\text{hierarchy} = 1 - \frac{P}{\max(P)}, \quad (6)$$

where  $P$  denotes the number of symmetrically reachable node pairs in the network;  $\max(P)$  denotes the maximum possible number of symmetrically reachable node pairs.

Network efficiency refers to the extent to which redundant connections exist in the network. In our spatial association network, the lower the network efficiency, the more the relationships between provinces and the more the spatial spillover channels for the development of digital financial inclusion. The calculation formula of network efficiency is as follows:

$$\text{efficiency} = 1 - \frac{Q}{\max(Q)}, \quad (7)$$

where  $Q$  represents the number of excess connections in the network;  $\max(Q)$  represents the maximum possible number of redundant connections.

**2.2.2. Centrality.** As for the locational characteristics of each province in the spatial association network of digital financial inclusion development, we focus on three aspects, namely, degree centrality, betweenness centrality, and closeness centrality [24], which can be used to measure the connectivity, intermediation, and accessibility [25] of different provinces in the network.

Degree centrality measures the extent to which a province is in direct contact or is adjacent to many other provinces in the network. It can be defined as the ratio of the number of provinces directly connected to a province to the number of provinces most likely to be directly connected to the province. Degree centrality can be calculated as follows:

$$C_{\text{deg}}(i) = \frac{n(i)}{N-1}, \quad (8)$$

where  $C_{\text{deg}}(i)$  denotes the degree centrality of province  $i$ ;  $n(i)$  denotes the number of provinces directly connected to the province  $i$  in the network;  $N$  represents the size of the network.

Betweenness centrality measures the extent to which a province is in the middle of other provinces in the network and reflects the degree of control of a province on the interconnection between other provinces. Its calculation formula is as follows:

$$C_{\text{btw}}(i) = \frac{2 \sum_J \sum_K b_{jk}(i)}{N^2 - (3N + 2)}, \quad (9)$$

where

$$b_{jk}(i) = \frac{d_{jk}(i)}{d_{jk}}, \quad (10)$$

where  $C_{\text{btw}}(i)$  represents the betweenness centrality of province  $i$ ;  $d_{jk}$  represents the number of shortest paths between provinces  $j$  and  $k$ ;  $d_{jk}(i)$  represents the number of shortest paths that pass through province  $i$  and connect provinces  $j$  and  $k$ ;  $N$  represents the size of the network.

Closeness centrality measures the closeness between provinces in the network and represents a measure not controlled by other provinces. If a province in the network is

close to all other provinces, that province has a high closeness centrality. The calculation formula of closeness centrality is as follows:

$$C_{\text{close}}(i) = \frac{\sum_{j=1}^N d_{ij}}{N-1}, \quad (11)$$

where  $C_{\text{close}}(i)$  denotes the closeness centrality of province  $i$ ;  $d_{ij}$  denotes the shortest path between provinces  $i$  and  $j$ ;  $N$  represents the size of the network.

**2.2.3. Block Model.** Block model analysis was first proposed by White, Boorman, and Breiger to better analyze the role and position of each province in the spatial association network [26]. On the basis of this method, 31 provinces can be divided into four blocks: the first one is the “primary beneficial” block. Its members have more relations within the block and fewer relations outside the block. The second one is the “net spillover” block. Its members mainly send out relations to other blocks. However, few relations are received from other blocks. The third one is the “bidirectional spillover” block, in which members send relations outside and inside the block. The fourth one is the “broker” block. Its members receive relationships from the members of the outside block and send them to the other block members; however, the internal members have relatively few connections.

Accordingly, we use UCINET software and the CONCOR method to divide the 31 provinces in the spatial association network of digital financial inclusion development into the four blocks mentioned above in this study.

### 2.3. Quadratic Assignment Procedure

**2.3.1. Theoretical Model.** On the one hand, digital finance can theoretically break through the limitations of traditional geographic space to provide people with financial services in remote areas cheaply and conveniently; on the other hand, the promotion of many businesses of digital finance still depends on geographical factors and its development also shows a robust spatial clustering [17]. Therefore, we speculate that the geographical adjacency may increase the probability of establishing the spatial association of digital financial inclusion development between provinces. Besides, as a new form of financial development, digital finance still follows the fundamental laws of financial development; that is, its development still relies on the real economy and traditional finance [27]. Meanwhile, the development of digital finance also depends to no small extent on the development of information technology [28] and mobile technology [1, 6, 11]. Moreover, tertiary industries have more digital finance demand than primary and secondary industries when considering the industrial structure. Hence, we speculate that the differences between provinces in terms of the development level of the economy, traditional finance and the Internet (PC Internet and mobile Internet), and the industrial structure may also affect the establishment of the spatial association of digital financial inclusion development between provinces.

In summary, we consider five kinds of factors to study the influencing factors of the spatial association of digital financial inclusion development. The specific information on these factors and their representative indicators is shown in Table 1.

Accordingly, we set up the following model:

$$R = f(S, E, F, N, M, I). \quad (12)$$

Equation (12) expresses the relationship between relational data, and these relational data consist of a series of matrices. The dependent variable  $R$  is the spatial association network of digital financial inclusion development; the corresponding spatial association matrix directly represents it. The independent variable  $S$  is the spatial adjacency matrix determined by the geographical location. If two provinces are adjacent in the spatial adjacency matrix, then the value is 1; otherwise, the value is 0. For the remaining variables, we take the average value of the corresponding indicator of each province during the sample period and then use the absolute difference of those average values to construct the difference matrix.

**2.3.2. QAP Analysis Method.** Given that our empirical data are relational, it contains attribute information and relational structure [29] and does not satisfy the assumption of “variable independence” in the sense of conventional statistics. Hence, most multivariate statistical methods cannot be used. In this study, we adopt a nonparametric QAP method, which can be used for hypothesis testing at the relationship-relationship level, to study the influencing factors of the spatial association network. QAP analysis includes QAP correlation analysis and QAP regression analysis.

QAP correlation analysis, which is based on the replacement of matrix data, is a method of comparing the similarity of the grid values in two square matrices and, at the same time, performing a nonparametric test [30]. The specific practice has the following three steps: first, the correlation coefficient between the long vectors formed by the known matrices is calculated. Next, the rows and corresponding columns of one matrix are randomly replaced simultaneously, and then the correlation coefficient between the replaced matrix and the other matrix is calculated. Repeating this process hundreds or even thousands of times obtains a distribution of correlation coefficients. Lastly, by comparing the actual correlation coefficient calculated in the first step with the distribution of the correlation coefficient calculated under random rearrangement, we can see whether the actual correlation coefficient falls into the rejection domain or the acceptance domain and then make a judgment.

The principle of QAP regression analysis is the same as that of QAP correlation analysis. The purpose of the QAP regression analysis is to study the regression relationship between multiple matrices and one matrix and evaluate the significance of the determination coefficient  $R^2$ . The specific calculation has two steps. First, regular multiple regression analysis is performed on the long vector corresponding to

the independent and dependent variable matrix. Secondly, the rows and corresponding columns of the dependent variable matrix are randomly permuted simultaneously, and then the regression is recalculated. This step is repeated hundreds or even thousands of times to estimate the standard error of the statistics.

**2.4. Data Sources.** The core data used in this study are the “Peking University Digital Financial Inclusion Index of China,” which is compiled on the basis of hundreds of millions of microdata from a representative digital financial institution in China; this dataset reflects the cross-section and cross-time changes in the acquisition and use of digital financial services in China [31]. The index covers 31 provinces, 337 prefecture-level cities (regions, autonomous prefectures, and leagues collectively referred to as “cities”), and nearly 2,800 counties (county-level cities, banners, and municipal districts collectively referred to as “counties”). The province-level and prefecture-level index span from 2011 to 2018, and the county-level index spans from 2014 to 2018. In addition to the overall index, the “Peking University Digital Financial Inclusion Index of China” also includes the coverage breadth subindex, the use depth subindex, and the digitization degree subindex [32]. Hence, the “Peking University Digital Financial Inclusion Index of China” can comprehensively portray the development trend of digital financial inclusion in different regions of China. However, to reflect the spatial association of China’s digital financial inclusion development from a general view, we only consider the provincial overall index in our study. The other QAP analysis data come from the “China Statistical Yearbook” and “China Financial Statistical Yearbook.” Besides, to remove the temporal trend, we also process the data logarithmically.

### 3. Analysis of Results

**3.1. Empirical Results and Analysis of the Spatial Association Network.** To study the structural and locational properties of spatial association network of digital financial inclusion development intuitively and clearly, we use NetDraw software to draw a diagram, as shown in Figure 1. From the figure, we can see that the associations between the 31 provinces are dense. Meanwhile, the developed eastern provinces are mainly located on the network’s right, whereas the central and western provinces are interwoven in the middle and left sides of the network.

**3.1.1. Whole Network Analysis.** The emphasis of the whole network analysis is on the structural characteristics of the spatial association network of digital financial inclusion development and its impact on the development of the provinces within the network.

Network density describes the number of spatial associations in the network. In the spatial association network of digital financial inclusion development, the maximum possible association between 31 provinces is 930, and the actual existing association is 359; hence, according to

TABLE 1: Variables and indicators.

Variable		Indicator	Variable description
Dependent variable	Network relations	Spatial association network of digital financial inclusion development ( $R$ )	Spatial association matrix of digital financial inclusion development
	Spatial adjacency relations	Spatial adjacency relation ( $S$ )	Spatial adjacency matrix
	Economic development level	Difference in per capita GDP ( $E$ )	Per capita GDP difference matrix
Independent variable	Traditional finance development level	Difference in the total credit balance of financial institutions per unit of GDP ( $F$ )	Total credit balance of financial institutions per unit of GDP difference matrix
	PC Internet development level	Difference in the Internet penetration rate ( $N$ )	Internet penetration rate difference matrix
	Mobile Internet development level	Difference in the mobile phone penetration rate ( $M$ )	Mobile phone penetration rate difference matrix
	Industrial structure	Difference in the tertiary industry output value per unit of GDP ( $I$ )	Tertiary industry output value per unit of GDP difference matrix

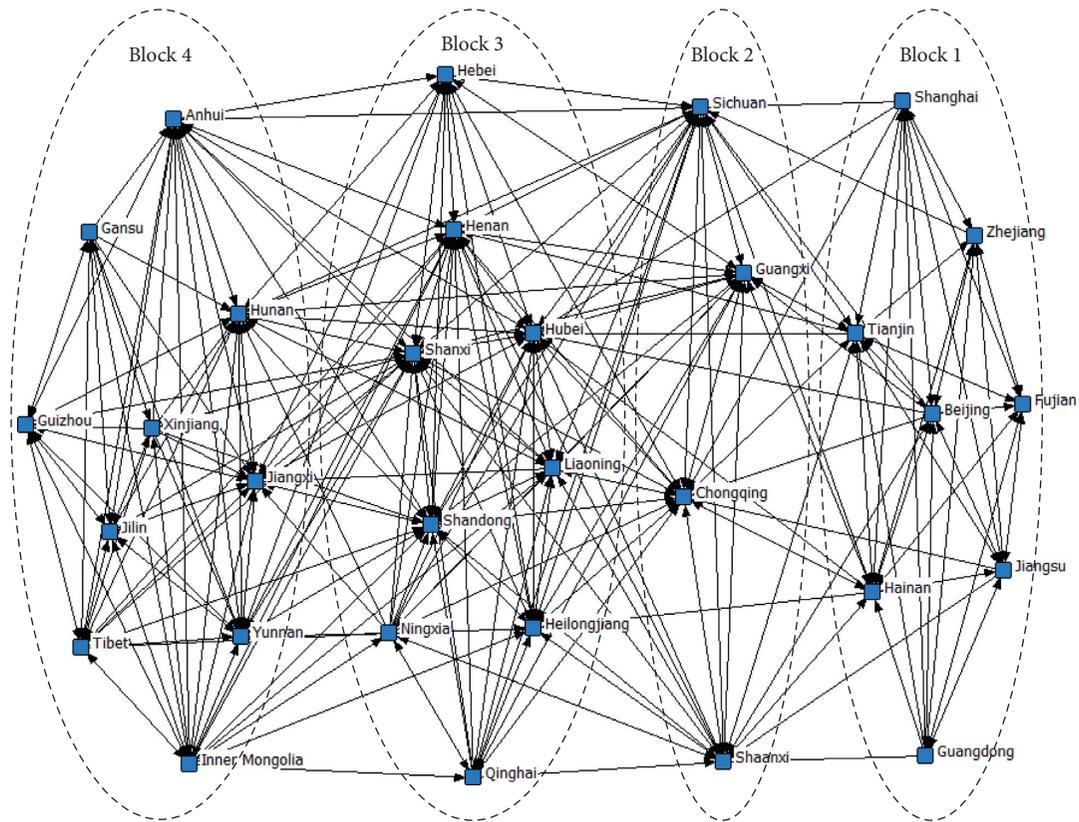


FIGURE 1: Spatial association network of China's digital financial inclusion development from 2011 to 2018.

formula (4), the network density is 0.386. This result reflects that the degree of interconnectedness between provinces regarding digital financial inclusion development is relatively low. It can be seen that the situation of direct and comprehensive communication and the mutually beneficial cooperation in terms of digital financial inclusion between provinces within the network are not optimistic.

Network connectedness, network hierarchy, and network efficiency describe the pattern of spatial associations in the network. On the basis of formulas (5)–(7), the network connectedness, network hierarchy, and network efficiency of the spatial association network for the digital financial inclusion development can be calculated. The network connectedness is 1, indicating that the network has a high relational degree and

good connectivity. In other words, this result implies that the provinces in the network can be directly and indirectly accessible to each other to a large extent. The network hierarchy is 0, indicating no hierarchical structure of spatial associations and spatial spillover effects between provinces in the network; that is, spatial associations and spatial spillover effects could also exist between provinces with the different development level of digital financial inclusion. The network efficiency is 0.577, indicating the existence of multiple overlapping overflow channels of digital financial inclusion development between provinces in the network; hence, the network structure is relatively stable. On the whole, the current spatial association pattern of high connectivity, nonhierarchy, and strong stability is very conducive to the exchange of information and the sharing of resources between provinces regarding the development of digital financial inclusion.

*3.1.2. Centrality Analysis.* Centrality analysis is to describe and measure the locational characteristics of each province in the spatial association network of the development of digital financial inclusion. Provinces that are more important or prominent in terms of connectivity, intermediation, and accessibility occupy the more central and vital location in the network.

Based on formula (8), the calculation results of degree centrality show that provinces with the degree centrality greater than 50 have the most considerable effect on other provinces in the development of digital financial inclusion. Besides, in terms of connectivity, these provinces are at the core of China's spatial association network of digital financial inclusion development. Among these provinces, the rapidly developing central and western provinces (Shanxi, Henan, Hubei, Sichuan, Hunan, Chongqing, Inner Mongolia, Anhui, Jiangxi, Guangxi, Shaanxi, and Ningxia) account for more than 85%. These provinces are in direct contact or are adjacent to many other provinces and could be recognized by other provinces as major channels to transmit digital financial inclusion development information. However, the degree centrality of eastern coastal provinces, such as Shanghai, Jiangsu, Zhejiang, Guangdong, and Fujian, is relatively low, which indicates that these economically developed provinces have limited direct or indirect spatial connections with other provinces in terms of digital financial inclusion development; hence, these provinces are in a relatively marginal location with respect to connectivity in the network. Part of the reason for this phenomenon lies with the fact that the aforementioned central and western provinces are located in the middle of China's geographic space. Therefore, relying on the geographical advantage of connecting east-west and north-south, these provinces can strengthen connections with more provinces in the development of digital financial inclusion, thereby establishing more spatial associations. In contrast, restricted by geographical conditions, the aforesaid eastern provinces have more connections with the central provinces and fewer connections with the western provinces. As a result, these provinces only establish the spatial associations of digital financial inclusion with fewer provinces.

According to the results of betweenness centrality calculated on the basis of formulas (9) and (10), the average betweenness centrality of 31 provinces is 29.548; the betweenness centrality of 15 provinces is higher than the average. Among them, the Shaanxi, Sichuan, and Shanxi provinces are the most critical nodes because they have the highest betweenness centrality. These three relatively fast-developing central and western provinces play an essential role in neighboring provinces and have a strong ability to control interprovincial digital financial inclusion development. In other words, these provinces are in the central location with respect to intermediation and play the critical "intermediary" and "bridge" role in the spatial association network, connecting the development of digital financial inclusion in eastern and western provinces. This phenomenon may be inseparable from the geographical advantage of these provinces. These provinces are located not only in the middle of China's geographic space but also along the Heihe-Tengchong Line which represents China's demographic, geographic, and economic boundaries. Therefore, relying on the advantage of "intermediary" and "bridge" in geographical location, these provinces occupy the central location in terms of intermediation and control the cooperation in digital financial inclusion between other provinces in the network. The betweenness centrality of Guizhou, Gansu, Jiangsu, Zhejiang, Qinghai, Fujian, Guangdong, and Xinjiang are all less than 5. Among them, half of the provinces are in the developed eastern region, whereas the other half is in the underdeveloped western region. However, these provinces all have relatively limited influence on neighboring provinces in the development of digital financial inclusion. This phenomenon may be caused by these provinces being located at the edge of China's geographic space; hence, they are not dominant geographically. This is also reflected in their location in the spatial association network; that is, these provinces are at the edge of the network, so they have weak abilities to control the digital financial inclusion cooperation between other provinces.

According to the calculation results of closeness centrality based on formula (11), the mean value of 31 provinces is 60.055; 15 provinces have a higher value than the average. Among them, rapidly developing central and western provinces (Shanxi, Hunan, Hubei, Sichuan, Guangxi, Chongqing, Hunan, Shaanxi, Ningxia, Heilongjiang, Anhui, Jiangxi, and Qinghai) account for more than 86%. These provinces are relatively close to other provinces in the spatial association network; that is, they can quickly interact with other provinces regarding digital financial inclusion development. Hence, these provinces occupy the central location with respect to accessibility of the spatial association network of digital financial inclusion development and are the central actors. It is worth noting that these provinces are almost the same as the central and western provinces with a degree centrality greater than 50. Therefore, these provinces that occupy the central location of the spatial association network can also be attributed to their superior location which connects east-west and north-south. Due to this locational advantage, these provinces can establish closer

spatial associations with other provinces in terms of digital financial inclusion development. The last ten provinces are Beijing, Shanghai, Xinjiang, Jilin, Guizhou, Zhejiang, Jiangsu, Guangdong, Gansu, and Fujian. Among these provinces, the eastern provinces account for 60%, and the central and western provinces account for 40%. However, they are all marginal actors in the spatial association network and may need to rely on other provinces to relay digital financial inclusion development information. This may also be because these provinces are located at the edge of China's geographic space (i.e., eastern and western regions). Therefore, they need to rely on the central provinces to establish spatial associations with other provinces.

It can be seen from the above analysis that some rapidly developing central and western provinces occupy the central location in terms of connectivity, intermediation, and accessibility in the spatial association network of China's digital financial inclusion development. In addition to being affected by geographical factors, we believe that this kind of locational characteristics of the spatial association network is also affected by policy factors to a certain extent. At the end of 2015, the Chinese government issued the "Plan for Promoting Inclusive Finance Development (2016–2020)," making more specific arrangements for inclusive finance development. Correspondingly, the Ministry of Finance of China began to implement the plan in 2016 by allocating special funds for the development of inclusive finance to all provinces. As shown in Figure 2, from 2016 to 2018, the Ministry of Finance of China mainly allocated special funds to provinces such as Yunnan, Henan, Shaanxi, Hubei, Jiangxi, Hunan, Guizhou, Gansu, Sichuan, and Anhui. These provinces are all located in the central and western regions of China, reflecting the Chinese government's strong support for developing inclusive finance in central and western provinces. Since digital financial inclusion is an essential direction of inclusive finance, the development of digital financial inclusion in central and western provinces accelerates accordingly, which helps these provinces establish more spatial associations with other provinces. Overall, the central and western provinces have occupied the central location in the spatial association network of China's digital financial inclusion development mainly due to their superior geographical location and strong government support.

**3.1.3. Block Model Analysis.** The focus of block model analysis is to identify and determine the role and position of each province in the spatial association network of the development of digital financial inclusion so as to find the "subgroups" in the network. Using UCINET software and setting the maximum segmentation depth and convergence criterion to 2 and 0.2, respectively, four digital financial inclusion development blocks can be obtained (as shown in Figure 1). Block 1 has eight members, all located in the economically developed eastern region, including Beijing, Tianjin, Jiangsu, Guangdong, Zhejiang, Hainan, Fujian, and Shanghai. Block 2 has four members, all of which are relatively fast-developing western provinces, namely, Guangxi, Chongqing, Sichuan, and Shaanxi. Block 3 has nine members, including provinces with strong economic growth (Hebei,

Shandong, Henan, Hubei, and Liaoning) and provinces with relatively slow economic growth (Qinghai, Shanxi, Heilongjiang, and Ningxia). Block 4 has ten members, mainly the relatively backward provinces in the central and western regions, namely, Jilin, Inner Mongolia, Hunan, Yunnan, Tibet, Guizhou, Gansu, Jiangxi, Anhui, and Xinjiang.

In the actual 359 associations in the spatial association network, the number of associations within the four blocks is 198, and the number of associations between the four blocks is 161, demonstrating the existence of spatial associations and spillover effects between the blocks. Specifically, according to Table 2, we can observe that Block 1 sends 24 relationships to other blocks but only receives 9 relationships from Block 2. The number of relationships that Block 1 sends out to the other blocks is approximately three times the number of relationships that is received from the other blocks. Therefore, Block 1 can be considered as a "net spillover" block. Block 2 receives 55 relationships from other blocks and simultaneously sends 40 relationships to other blocks; however, there are only a few relationships between the internal members of Block 2. Therefore, Block 2 is a typical "broker" block. Block 3 sends 60 relationships to other blocks and receives 69 relationships from other blocks; the expected internal relation ratio is 26.67%, and the actual internal relation ratio is 48.72%. Hence, Block 3 fits the condition of a "primary beneficiary" block. Block 4 sends 75 relationships within the block and 37 relationships to other blocks. The expected internal relation ratio is 30.00%, and the actual internal relation ratio is 66.96%. Thus, Block 4 meets the condition of a "bidirectional spillover" block.

According to the distribution of the associations between blocks, the density matrix (as shown in Table 3) can be calculated to reflect the distribution of spillover effects among blocks. With the entire network density being 0.386, there will be a tendency to concentrate in the block when the density of one block is greater than 0.386. Hence, by assigning a value greater than 0.386 in the density matrix as 1, otherwise, assigning as 0, the image matrix as shown in Table 4 can be obtained. The image matrix can clearly show the spillover effects between blocks. According to Tables 3 and 4, we can observe that the spillover effect of Block 1 is mainly reflected in itself and Block 2, that of Block 2 is mainly reflected in itself and Block 3, and that of Block 3 is mainly reflected in itself and Block 2. By contrast, the spillover effect of Block 4 is only reflected in itself.

The image matrix also clearly shows the transmission mechanism of the development of digital financial inclusion in China. Figure 3 shows that, first of all, the development of China's digital financial inclusion has a noticeable "club" effect. This indicates that abundant associations exist within each block; that is, the members within the block are closely related to each other. Second, Block 1 is the engine for the development of China's digital financial inclusion and transmits the development's momentum to Block 2. Third, as an important "bridge" and "link," Block 2 transmits the development's momentum to Block 3. And next, part of the development's momentum is returned to Block 2 by Block 3. Hence, it can be seen that this transmission mechanism has the characteristics of gradient spillover and bidirectional spillover. Overall, the members of Block 1 (Beijing, Tianjin, Jiangsu, Guangdong, Zhejiang, Hainan, Fujian, and

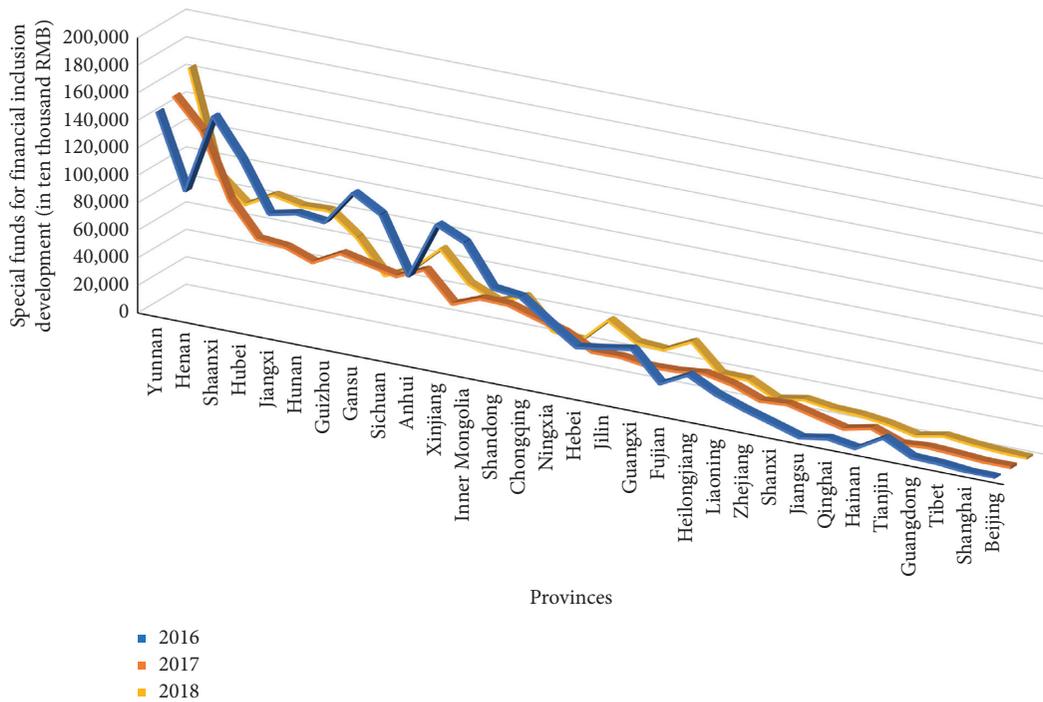


FIGURE 2: The allocation of special funds for financial inclusion development in various provinces in China from 2016 to 2018.

TABLE 2: Analysis of spillover effects between various blocks.

Block	Block 1	Block 2	Block 3	Block 4	Block membership	Expected internal relation ratio (%)	Actual internal relation ratio (%)	Total relations received from other blocks	Total relations sent to other blocks	Block role
Block 1	54	18	6	0	8	23.33	69.23	9	24	Net spillover
Block 2	9	12	29	2	4	10.00	23.08	55	40	Broker
Block 3	0	34	57	26	9	26.67	48.72	69	60	Primary beneficial
Block 4	0	3	34	75	10	30.00	66.96	28	37	Bidirectional spillover

TABLE 3: Density matrix of the blocks.

	Block 1	Block 2	Block 3	Block 4
Block 1	0.964	0.563	0.083	0.000
Block 2	0.281	1.000	0.806	0.050
Block 3	0.000	0.944	0.792	0.289
Block 4	0.000	0.075	0.378	0.833

TABLE 4: Image matrix of the blocks.

	Block 1	Block 2	Block 3	Block 4
Block 1	1	1	0	0
Block 2	0	1	1	0
Block 3	0	1	1	0
Block 4	0	0	0	1

Shanghai) serving as the engine are all located in the developed eastern region with rapid economic growth and financial development. Therefore, these provinces can lead other provinces in the development of digital financial inclusion based on their economic and financial development advantages. However, the driving effect of Block 1 on Block 3 (economically developed areas and economically backward areas) is not directly realized but indirectly realized through Block 2 (relatively fast-developing western provinces).

**3.1.4. Method Effectiveness Analysis.** In graph theory, Minimum Spanning Tree (MST) is a standard approach used to describe network structure. A network constructed based on the MST approach can intuitively reflect the most critical connections and information between nodes in the network with the simplest structure [20, 33, 34]. Therefore, we refer to

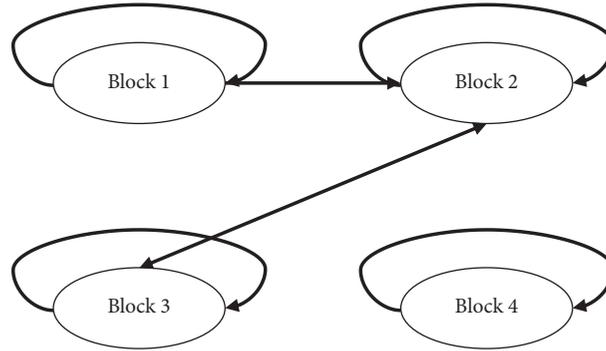


FIGURE 3: Relationship between China's four digital financial inclusion development blocks.

the work of Yang and Liu [21] and verify the effectiveness of our method of constructing the network mentioned above by establishing a network based on the MST method. The basis of the network, which is constructed on the basis of the MST method, is also the correlation coefficient. After calculating the correlation coefficient in accordance with equation (2), we can convert it into Euclidean distance in accordance with equation (1). Then, we can use Prim's algorithm to construct MST [35].

The concise network of digital financial inclusion development in China built based on the MST method is shown in Figure 4. Figure 4 provides some convincing information. Except for Chongqing, the role and position of other provinces in the network constructed based on the MST method are basically the same as before. In this tree structure, the eight developed eastern provinces (i.e., Guangdong, Jiangsu, Fujian, Beijing, Zhejiang, Shanghai, Tianjin, and Hainan) are clustered in Block 1 on the upper right. Block 2 connected to Block 1 includes three relatively fast-developing western provinces, that is, Shaanxi, Guangxi, and Sichuan. Their structure of association is relatively simple. As a critical node, Hebei is connected to Blocks 3 and 4. Compared with the previous network, besides five provinces with strong economic growth (Hebei, Shandong, Henan, Hubei, and Liaoning) and four provinces with relatively slow economic growth (Qinghai, Shanxi, Heilongjiang, and Ningxia), Block 3 also includes Chongqing which used to belong to Block 2. Block 4 is the same as before and mainly includes Jilin, Inner Mongolia, Hunan, Yunnan, Tibet, Guizhou, Gansu, Jiangxi, Anhui, and Xinjiang, which are relatively underdeveloped central and western provinces. Moreover, Block 1 and Block 3 are not directly connected but indirectly connected through Block 2.

In conclusion, by comparing the network constructed based on our method with the network constructed based on the MST approach, we find that the role and position of the provinces in the network are basically the same as before. Therefore, the effectiveness of our network construction method is well confirmed.

### 3.2. Influencing Factors of the Spatial Association Network

**3.2.1. QAP Correlation Analysis.** We use UCINET software and select 5000 random permutations to test the correlation

between the spatial association matrix and the matrices of the influencing factors, and the results obtained are shown in Table 5. In Table 5, "Value" represents the actual correlation coefficients between the spatial association matrix and the influencing factor matrices; "Significance" represents the significance level; "Average" and "Std. dev" represent the average value and the standard deviation of the correlation coefficients calculated from 5000 random permutations; "Min" and "Max" denote the minimum and maximum values in the randomly calculated correlation coefficients; "Prop  $\geq 0$ " and "Prop  $\leq 0$ " indicate the probability that the correlation coefficients of these random calculations are no less than and no more than the actual correlation coefficients, respectively.

The QAP correlation analysis results show a significantly positive correlation between the spatial association matrix  $R$  and the spatial adjacency matrix  $S$ , with a correlation coefficient of 0.123. This result indicates that the geographical adjacency between provinces has a significantly positive effect on the spatial association and spatial overflow between provinces. The correlation coefficients between the spatial association matrix  $R$  and the other difference matrices reflecting the development level of the economy, traditional finance and the Internet (PC Internet and mobile Internet), and the industrial structure are all significantly negative. This result means that these four kinds of critical factors also affect the spatial association and spatial spillover between provinces.

Furthermore, we perform a QAP correlation analysis on the matrices of the influencing factor. The results in Table 6 show that the matrices of influencing factors are highly correlated and statistically significant. Therefore, the effect of these influencing factors on spatial association matrix  $R$  may overlap, which is a characteristic of relational data. Hence, we must use the QAP method to deal with the "multicollinearity" problem between these relational data.

**3.2.2. QAP Regression Analysis.** We use UCINET software and select 5000 random permutations to test the effect of the matrices of various influencing factors on the spatial association matrix  $R$ , and the results obtained are shown in Tables 7 and 8. The model-fitting results in Table 7 show that the determination coefficient is 0.142, and its adjusted value is 0.137. This result indicates that when a linear relationship

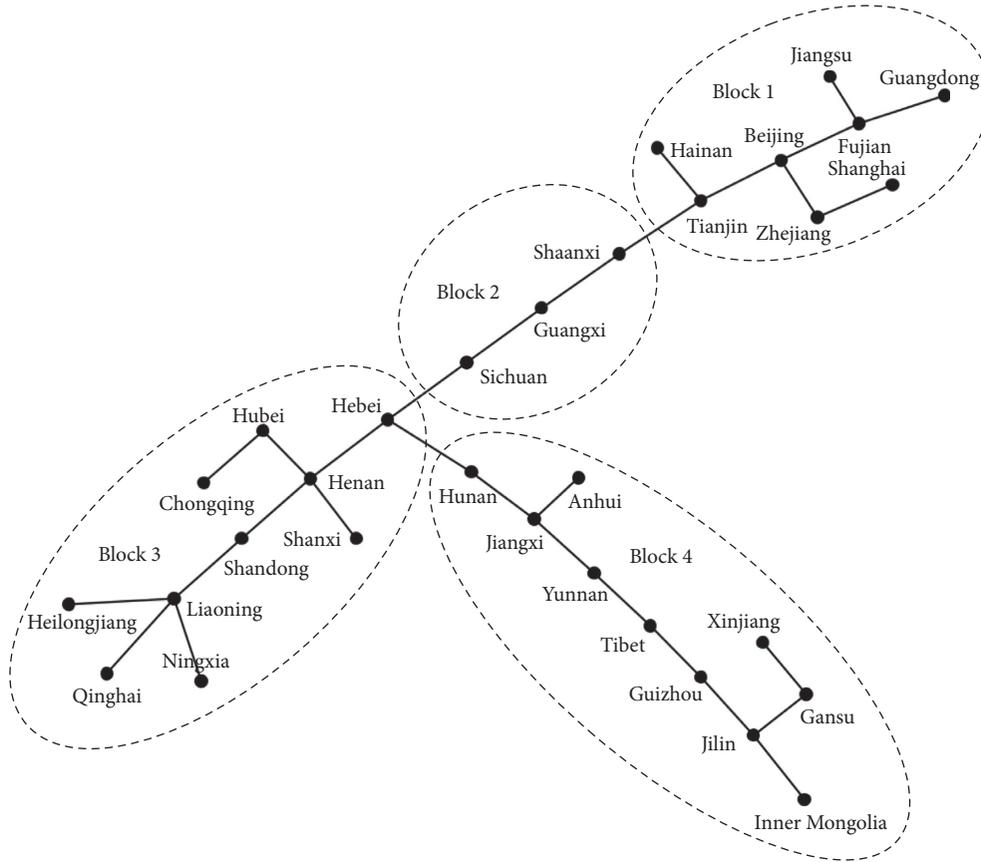


FIGURE 4: Network structure of digital financial inclusion development in China from 2011 to 2018 based on the MST approach.

TABLE 5: QAP correlation analysis of spatial association matrix  $R$  and its influencing factor matrices.

Variable	Value	Significance	Average	Std. dev	Min	Max	Prop $\geq 0$	Prop $\leq 0$
$S$	0.123***	0.007	0.000	0.043	-0.151	0.166	0.007	0.995
$E$	-0.315***	0.000	-0.001	0.050	-0.207	0.138	1.000	0.000
$F$	-0.098**	0.038	-0.000	0.051	-0.257	0.136	0.963	0.038
$N$	-0.335***	0.000	-0.000	0.051	-0.270	0.137	1.000	0.000
$M$	-0.246***	0.000	-0.001	0.054	-0.205	0.157	1.000	0.000
$I$	-0.109**	0.021	0.000	0.056	-0.172	0.154	0.980	0.021

Note. \*\*\* and \*\* denote significance at 1% and 5% levels, respectively.

exists between the spatial association matrix  $R$  and the influencing factor matrices that we considered in this study, the matrices of the influencing factors with a significant influence can explain 13.7% of the variation of the spatial association matrix  $R$ .

The regression coefficients and the test indicators of each variable are shown in Table 8. In Table 8, “Unstandardized coefficient” and “Standardized coefficient” represent the unstandardized and standardized regression coefficients of the variable matrices; “Significance” represents the significance level; “Prop  $\geq 0$ ” and “Prop  $\leq 0$ ” indicate the probability that these randomly calculated regression coefficients are no less than and no more than the actual regression coefficients, respectively. The results show that the regression coefficients of difference matrices  $N$  and  $E$ ,  $-0.236$  and  $-0.171$ , are both significantly negative at the 1% significance

level, indicating that when the difference of the development level of the PC Internet and economy decreases by 1%, the probability of establishing the spatial association between two provinces can be increased by 0.236% and 0.171%, respectively. The regression coefficient of difference matrix  $I$  is 0.195 and significant at the 1% significance level, indicating that when the industrial structure’s difference increases by 1%, the probability of building two provinces’ spatial association can be increased by 0.195%. The regression coefficient of spatial adjacency matrix  $S$  is 0.062 and significant at the 10% significance level, indicating that if two provinces are adjacent, the probability of establishing the spatial association between these two provinces can be increased by 0.062%, whereas the regression coefficients of difference matrices  $M$  and  $F$  are insignificant, indicating that the difference in the development level of the mobile Internet

TABLE 6: QAP correlation analysis between influencing factors matrices.

Variable	<i>S</i>	<i>E</i>	<i>F</i>	<i>N</i>	<i>M</i>	<i>I</i>
<i>S</i>	1.000***	-0.148***	-0.115***	-0.151***	-0.108***	-0.079**
<i>E</i>	-0.148***	1.000***	0.270***	0.710***	0.550***	0.453***
<i>F</i>	-0.115***	0.270***	1.000***	0.324***	0.476***	0.667***
<i>N</i>	-0.151***	0.710***	0.324***	1.000***	0.790***	0.546***
<i>M</i>	-0.108***	0.550***	0.476***	0.790***	1.000***	0.723***
<i>I</i>	-0.079**	0.453***	0.667***	0.546***	0.723***	1.000***

Note. \*\*\* and \*\* denote significance at 1% and 5% levels, respectively.

TABLE 7: Results of model fitting.

$R^2$	Adjusted $R^2$	Observations	Permutations
0.142	0.137	930	5000

TABLE 8: QAP regression results of spatial association matrix  $R$  and its influencing factor matrices.

Variable	Unstandardized coefficient	Standardized coefficient	Significance	Prop $\geq 0$	Prop $\leq 0$
Interception	0.386	0.000	—	—	—
<i>S</i>	0.085	0.062*	0.061	0.061	0.940
<i>E</i>	-0.247	-0.171***	0.006	0.994	0.006
<i>F</i>	-0.095	-0.066	0.117	0.883	0.117
<i>N</i>	-1.136	-0.236***	0.005	0.995	0.005
<i>M</i>	-0.002	-0.068	0.210	0.791	0.210
<i>I</i>	1.087	0.195***	0.007	0.007	0.994

Note. \*\*\* and \* denote significance at 1% and 10% levels, respectively.

and traditional finance has almost no effect on the spatial association between provinces.

#### 4. Conclusions and Implications

This study constructs a spatial association network of digital financial inclusion development and uses the network analysis method and the QAP method to analyze the network's structural and locational properties and the influencing factors. Concretely, we first set up a spatial association network based on the Euclidean distance; then, we study the structural and locational properties of the network and the role and position of the provinces within the network through the analysis of the whole network, centrality, and block model; lastly, we explore the influencing factors of the spatial association by using the QAP method. According to the research results, we draw the following conclusions:

- (1) The spatial association network of China's digital financial inclusion development has high connectivity, nonhierarchy, and strong stability; however, its density is relatively low. Hence, further communication and cooperation between provinces to develop digital financial inclusion can still be promoted. The centrality of some rapidly developing central and western provinces located in the middle of China's geographic space is relatively high. By contrast, the centrality of some developed eastern provinces is relatively low. We believe that this result

is mainly affected by geographical factors and policy factors. On the one hand, based on the geographical advantage of connecting east-west and north-south, these rapidly developing central and western provinces are able to establish spatial associations with more provinces for the development of digital financial inclusion. On the other hand, relying on the strong support of the Chinese government, digital financial inclusion in the central and western provinces has made considerable progress, which has also promoted the establishment of spatial associations with more provinces.

- (2) Provinces in the spatial association network of China's digital financial inclusion development can be roughly divided into four blocks. As a net spillover block, Block 1 includes eight developed eastern provinces: Beijing, Tianjin, Jiangsu, Guangdong, Zhejiang, Hainan, Fujian, and Shanghai. Block 2 plays the role of the broker and is composed of four relatively fast-developing western provinces, which are located in the middle of China's geographic space (i.e., Guangxi, Chongqing, Sichuan, and Shaanxi). Block 3 is the primary beneficiary block, including provinces with strong economic growth (i.e., Hebei, Shandong, Henan, Hubei, and Liaoning) and provinces with relatively slow economic growth (i.e., Qinghai, Shanxi, Heilongjiang, and Ningxia). Block 4 consists of relatively backward provinces in the central and western regions (i.e., Jilin, Inner

Mongolia, Hunan, Yunnan, Tibet, Guizhou, Gansu, Jiangxi, Anhui, and Xinjiang) and plays the role of bidirectional spillover in the network. Among the four blocks, Block 1 is the engine that promotes the digital financial inclusion development in China, and its driving effect on Block 3 is not directly realized but indirectly realized through Block 2.

- (3) The similarity in the development level of the PC Internet and economy, the difference in the industrial structure, and the spatial adjacency are the main influencing factors of the interprovincial spatial association of China's digital financial inclusion development. On the contrary, the interprovincial spatial association of China's digital financial inclusion development is hardly affected by the development level of the mobile Internet and traditional finance. Among these influencing factors, it is worth noting that, first of all, spatial adjacency is still an important factor affecting the spatial association. This reflects that although digital financial inclusion can break through the limitations of time and space, its development is still influenced by the geographical factor to some extent. Second, the development level of traditional finance hardly affects the spatial association, indicating that although digital financial inclusion still follows the essence of financial development, its development does not mainly depend on the development level of traditional finance.

The policy implications of the conclusion are as follows: First of all, based on the characteristics of low density, high connectivity, nonhierarchy, and strong stability of spatial association network of China's digital financial inclusion development, policymakers can further strengthen the communication and docking among provinces and actively establish consultation and cooperation mechanism so as to effectively promote the information exchange and resources sharing of digital financial inclusion development among provinces. Second, policymakers can highlight the central position of the rapidly developing central and western provinces represented by Shanxi, Sichuan, Hunan, and Hubei in terms of connectivity, intermediation, and accessibility in the spatial association network of China's digital financial inclusion development. On the one hand, policymakers can fully tap the potential of these provinces in transmitting the information of digital financial inclusion development. On the other hand, policymakers can give full play to the role of these provinces as the "bridge" and "link" in promoting the coordinated development of digital financial inclusion among provinces. Third, policymakers can bring the radiating and leading role of the eastern developed provinces in the spatial association network of China's digital financial inclusion development into full play. By disseminating the valuable experience and feasible path of developing digital financial inclusion in the developed eastern provinces to the central and western provinces, it will drive and help the central and western provinces develop digital financial inclusion. Lastly, in order to increase the

probability of establishing the spatial association between provinces and amplify the interprovincial spatial spillover effect, policymakers can make efforts in several ways, including comprehensively increasing the national PC Internet penetration rate, promoting the coordinated development of regional economies, and forming an interprovincially differentiated industrial structure.

Although we have conducted a relatively comprehensive analysis, our research still has limitations in some aspects. First, limited by the data, we have not investigated the evolutionary characteristics of the spatial association network from a dynamic perspective and have only merely described the static characteristics. Hence, we will conduct dynamic evolution research on the spatial association network in the future. In addition to Euclidean distance, we can consider using other spatial metrics as the distance to construct network connections. We can then compare and analyze networks with different spatial metrics to further understand digital financial inclusion development's spatial association.

## Data Availability

The core data used to support the findings of the study are the "Peking University Digital Financial Inclusion Index of China," which is compiled by the Institute of Digital Finance, Peking University. The data can be accessed from <https://idf.pku.edu.cn/yjcg/zsbg/485016.htm>.

## Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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## References

- [1] A. Demircuc-Kunt, L. Klapper, D. Singer, S. Ansar, and J. Hess, *The Global Findex Database 2017: Measuring Financial Inclusion and the Fintech Revolution*, World Bank, Washington, DC, USA, 2018.
- [2] D. Gabor and S. Brooks, "The digital revolution in financial inclusion: international development in the fintech era," *New Political Economy*, vol. 22, no. 4, pp. 423–436, 2016.
- [3] K. Lauer and T. Lyman, *Digital Financial Inclusion: Implications for Customers, Regulators, Supervisors, and Standard-Setting Bodies*, Consultative Group to Assist the Poor, Washington, DC, USA, 2015.
- [4] T. Sun, "Balancing innovation and risks in digital financial inclusion-experiences of ant financial services group," in *Handbook of Blockchain, Digital Finance, and Inclusion Volume*, Academic Press, Cambridge, MA, USA, 2018.
- [5] World Bank, *Global Financial Development Report 2014: Financial Inclusion*, World Bank Publications, Washington, DC, USA, 2013.

- [6] J. Manyika, S. Lund, M. Singer, O. White, and C. Berry, *Digital Finance for All: Powering Inclusive Growth in Emerging Economies*, McKinsey Global Institute, San Francisco, CA, USA, 2016.
- [7] L. Yang and Y. Zhang, “Digital financial inclusion and sustainable growth of small and micro enterprises—evidence based on China’s new third board market listed companies,” *Sustainability*, vol. 12, no. 9, p. 3733, 2020.
- [8] J. Li, Y. Wu, and J. J. Xiao, “The impact of digital finance on household consumption: evidence from China,” *Economic Modelling*, vol. 86, pp. 317–326, 2020.
- [9] Q. Song, J. Li, Y. Wu, and Z. Yin, “Accessibility of financial services and household consumption in China: evidence from micro data,” *The North American Journal of Economics and Finance*, vol. 53, Article ID 101213, 2020.
- [10] Z. Yin, X. Gong, P. Guo, and T. Wu, “What drives entrepreneurship in digital economy? Evidence from China,” *Economic Modelling*, vol. 82, pp. 66–73, 2019.
- [11] S. Gammage, A. Kes, L. Winograd et al., *Gender and Digital Financial Inclusion: What Do We Know and What Do We Need to Know*, International Center for Research on Women, Washington, DC, USA, 2017.
- [12] X. Wang and G. He, “Digital financial inclusion and farmers’ vulnerability to poverty: evidence from rural China,” *Sustainability*, vol. 12, no. 4, p. 1668, 2020.
- [13] D. Radcliffe and R. Voorhies, “A digital pathway to financial inclusion,” *SSRN Electronic Journal*, Article ID 2186926, 2012.
- [14] P. K. Ozili, “Impact of digital finance on financial inclusion and stability,” *Borsa Istanbul Review*, vol. 18, no. 4, pp. 329–340, 2018.
- [15] M. N. A. Siddik and S. Kabiraj, “Digital finance for financial inclusion and inclusive growth,” in *Digital Transformation in Business and Society*, Springer, Berlin, Germany, 2020.
- [16] X. Wang and J. Guan, “Financial inclusion: measurement, spatial effects and influencing factors,” *Applied Economics*, vol. 49, no. 18, pp. 1751–1762, 2017.
- [17] F. Guo, J. Wang, F. Wang et al., “Measuring China’s digital financial inclusion: index compilation and spatial characteristics,” *Jingjixue Jikan (China Economic Quarterly)*, vol. 19, no. 4, pp. 1401–1418, 2019.
- [18] Y. Shen, C. J. Hueng, and W. Hu, “Measurement and spillover effect of digital financial inclusion: a cross-country analysis,” *Applied Economics Letters*, pp. 1–6, 2020.
- [19] L. Li, “China will become the world’s largest digital financial market,” 2020, [https://k.sina.com.cn/article\\_6465571420\\_18160ca5c01900n1y5.html?from=movie](https://k.sina.com.cn/article_6465571420_18160ca5c01900n1y5.html?from=movie).
- [20] R. N. Mantegna, “Hierarchical structure in financial markets,” *The European Physical Journal B*, vol. 11, no. 1, pp. 193–197, 1999.
- [21] C. Yang and S. Liu, “Spatial correlation analysis of low-carbon innovation: a case study of manufacturing patents in China,” *Journal of Cleaner Production*, vol. 273, Article ID 122893, 2020.
- [22] D. Krackhardt, “Graph theoretical dimensions of informal organizations,” *Computational Organization Theory*, vol. 89, no. 112, pp. 123–140, 1994.
- [23] M. Dozier, M. Harris, and H. Bergman, “Social network density and rehospitalization among young adult patients,” *Psychiatric Services*, vol. 38, no. 1, pp. 61–65, 1987.
- [24] L. C. Freeman, “Centrality in social networks conceptual clarification,” *Social Networks*, vol. 1, no. 3, pp. 215–239, 1978.
- [25] S. Chen, J. Xi, M. Liu, and T. Li, “Analysis of complex transportation network and its tourism utilization potential: a case study of Guizhou expressways,” *Complexity*, vol. 2020, Article ID 1042506, 22 pages, 2020.
- [26] H. C. White, S. A. Boorman, and R. L. Breiger, “Social structure from multiple networks. I. Blockmodels of roles and positions,” *American Journal of Sociology*, vol. 81, no. 4, pp. 730–780, 1976.
- [27] F. Guo, S. T. Kong, and J. Wang, “General patterns and regional disparity of internet finance development in China: evidence from the Peking University Internet finance development index,” *China Economic Journal*, vol. 9, no. 3, pp. 253–271, 2016.
- [28] J. Xu, “China’s internet finance: a critical review,” *China & World Economy*, vol. 25, no. 4, pp. 78–92, 2017.
- [29] J. Neville, M. Adler, and D. Jensen, “Clustering relational data using attribute and link information,” in *Proceedings of the Text Mining and Link Analysis Workshop, 18<sup>th</sup> International Joint Conference on Artificial Intelligence*, Acapulco, Mexico, August 2003.
- [30] M. Everett, *Social Network Analysis, Textbook at Essex Summer School in SSDA*, LinkedIn, Mountain View, CA, USA, 2002.
- [31] J. T. Lai, I. K. M. Yan, X. Yi, and H. Zhang, “Digital financial inclusion and consumption smoothing in China,” *China & World Economy*, vol. 28, no. 1, pp. 64–93, 2020.
- [32] F. Guo, T. Kong, J. Wang et al., *The Peking University Digital Financial Inclusion Index of China (2011–2018)*, Institute of Digital Finance, Peking University, Beijing, China, 2019.
- [33] Q. Ji and Y. Fan, “Evolution of the world crude oil market integration: a graph theory analysis,” *Energy Economics*, vol. 53, pp. 90–100, 2016.
- [34] J.-P. Onnela, A. Chakraborti, K. Kaski, J. Kertesz, and A. Kanto, “Dynamics of market correlations: taxonomy and portfolio analysis,” *Physical Review E*, vol. 68, no. 5, Article ID 056110, 2003.
- [35] H. Marfatia, W.-L. Zhao, and Q. Ji, “Uncovering the global network of economic policy uncertainty,” *Research in International Business and Finance*, vol. 53, Article ID 101223, 2020.