



Differential effects of tourism industry spatial distribution under different levels of digital economy development: A multidimensional analysis of spatial Dubin Model

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SUMMARY: *The expansion of digital infrastructure, platform-based services and online tourism consumption has reshaped the regional organization of tourism resources, yet its influence on tourism spatial distribution may vary across different stages of digital economy development. Using panel observations from 30 Chinese provinces during 2012–2022, the study builds a digital economy development index and a tourism spatial distribution index, and then applies a spatial Dubin model to identify local effects, neighboring spillovers and staged heterogeneity. Across the three digital economy groups, the tourism spatial distribution index increased from 0.521, 0.358 and 0.247 in 2012 to 0.714, 0.533 and 0.386 in 2022, showing that tourism agglomeration improved under all digital development stages. The overall effect of digital economic growth is 0.164, the spatial lag coefficient is 0.287, the direct effect is 0.172, and the indirect effect is 0.104. The findings indicate a stage-dependent mechanism: low-level regions benefit more from neighboring digital spillovers, whereas high-level regions mainly rely on local digital infrastructure, platform integration and governance capacity to strengthen tourism agglomeration.*

KEYWORDS: *Digital economy; Spatial distribution of tourism industry; Spatial Dubin Model; Spatial spillover effect*

1 Introduction

The development of digital economy has changed how tourism resources are matched, promoted and connected across regions, especially through online platforms, smart service systems, digital finance and data-driven destination management. Tourism activities usually operate through cross-regional flows of visitors, information, transport services and supporting industries, which makes the spatial pattern of one province closely related to surrounding provinces. A province with stronger tourism services may influence nearby regions through visitor movement, shared routes, online promotion and cross-regional industrial cooperation. Therefore, research on digital economy and tourism should move beyond aggregate growth effects and further examine how digital factors reshape regional interaction, spatial dependence and cross-provincial diffusion. Tang et al. Based on the empirical study of China, it concluded that the digitization process has a significant role in promoting the development of tourism [1]. Liu & Kim, on the other hand, investigated the impact of digital economy development on tourism demand from the perspective of spatial spillover effect, and believed that digital economy could not only affect tourism demand in the region, but also induce changes in surrounding markets through regional interaction

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mechanisms [2]. Finally, Tang also found that the digital economy enhances the resilience of the tourism economy, and to some extent improves the resilience and adaptability of the tourism system under external shocks [3].

Existing studies on digital economy and tourism can be divided into three lines: tourism growth effects, tourism efficiency improvement and spatial spillover mechanisms. Wu et al. examined the linkage between digital economy and tourism from the perspectives of mechanism, causal identification and spatial spillover, which provides a basis for understanding the multi-channel transmission of digital factors in tourism systems [4]. Li et al. focused on digital financial inclusion and showed that payment convenience, consumption accessibility and service coverage can reshape domestic tourism demand across regions [5]. Ji et al. believe that the development of smart city can promote the development of tourism through information governance, information provision and facility integration [6]. According to the research of Zhang and Cheng, digitalization can improve the tourism efficiency to a certain extent, and there are obvious spatial heterogeneity characteristics between different regions, and different absorptive capacity and transformation paths [7]. Other studies further extend the discussion to enterprise productivity, employment expansion, platform-based industrial restructuring and environmental consequences of tourism firms [8-11]. These works indicate that digital economy affects tourism not through a single growth channel, but through the combined adjustment of enterprise operation, labor demand, platform organization and green transition.

At the same time, the spatial pattern of tourism and its related driving factors have been continuously studied. Ma et al. concluded obvious agglomeration effect based on the study on the spatial pattern and driving factors of tourism demand in Chinese provinces [12]. Wang et al. used Social Network Analysis (SNA) and GIS to explore the evolution trend of tourism flow network in the Yangtze River Delta region, which indicated that tourism connection had transitioned from single competition to network cooperation [13]. Li et al.'s study on China's rural tourism flow network found that node link strength was closely related to regional resource conditions and traffic conditions [14]. Cao and Liu pointed out that the tourism development of big cities has obvious spatial spillover effect, which may affect the tourism development pattern of surrounding regions [15]. Shi et al. proposed that the construction of high-speed railway would cause significant changes in the spatial organization form of tourism flow in China [16], while Li et al. verified that high-speed railway connection could effectively reconstruct cross-regional tourism flow [17]. Li and Pu also pointed out that the influence of overseas students would also be reflected in inbound tourism, and proposed relevant determinants of inbound tourism and spatial diffusion utility, the spatial distribution of tourism is the result of the comprehensive effect of multiple factors [18, 19]. Zhang et al. studied the spatio-temporal evolution of China's coastal tourism economy and its driving factors [20]; Chen et al. analyzed the impact of tourism development on urban well-being and its spatial spillover effect [21]; Zhang et al. et al. constructed the coordinated development evaluation system of Guangdong Province's tourism performance and development level from the perspective of high-quality development [22]. Some important results from this literature are summarized in Table 1 as follows.

Table 1: Review of related studies

Researcher	Research Topic or Method	Research Object	Relevance to This Study
Tang et al. [1]	Digital economy and urban tourism development	Chinese cities	Provides evidence for the growth effect of digital economy, but does not distinguish spatial responses by digital development level.
Liu and Kim [2]	Spatial spillover analysis	Regional tourism demand in China	Supports the use of spatial spillover analysis in tourism research.
Tang [3]	Tourism economic resilience research	China's tourism economy	Suggests that digital capacity may affect tourism stability under external shocks.
Wu et al. [4]	Mechanisms, causality, and spatial spillovers	China's tourism industry	Indicates that digital economy should be examined through more than one transmission channel.
Li et al. [5]	Digital inclusive finance and tourism demand	China's domestic tourism market	Shows that financial digitalization may create cross-regional tourism effects.
Ji et al. [6]	Smart cities and tourism empowerment	Chinese cities	Suggests that urban digital governance can support tourism service upgrading.
Zhang and Cheng [7]	Spatiotemporal effect research	Provincial tourism efficiency in China	Provides a basis for grouping provinces by digital development level.
Ma et al. [12]	Analysis of spatial pattern and driving factors	Provincial tourism demand in China	Confirms the need to examine tourism distribution from a spatial perspective.
Cao and Liu [15]	Spatial spillover effect research	Tourism in China's megacities	Provides a basis for introducing spatial lag terms into the empirical model.
Zhang et al. [20]	Spatiotemporal evolution and driving factor analysis	Coastal tourism economy in China	Supports the need to compare tourism spatial changes across regions.

Overall, previous research has clarified the contribution of digital economy to tourism growth, efficiency, resilience and employment. However, most empirical studies still estimate an average digital effect for the full sample, while the spatial responses of tourism under low-, middle- and high-level digital economy conditions remain insufficiently compared. In addition, existing spatial studies mainly focus on tourism demand, efficiency or flow networks, and pay less attention to whether digital infrastructure, platform coverage and digital governance capacity produce different local and neighboring effects. This gap provides the basis for introducing grouped Spatial Dubin Model estimation in this study.

On this basis, this study uses Chinese provincial tourism data to measure tourism spatial distribution and digital economy development separately, and then introduces a spatial Dubin framework to compare direct effects, indirect effects and total effects across different digital

economy levels. This study aims to clarify how tourism spatial patterns evolve under hierarchical digital economy conditions and to provide spatial evidence for promoting coordinated regional tourism development through digital transformation.

2 Methods and data sources

To examine how digital economy levels condition tourism spatial distribution, the empirical design combines provincial sample construction, multi-source indicator processing and spatial econometric testing within the same analytical framework. Since spatial measurement has strong requirements for the integrity of regionalization, the continuity of variables and the integrity of periods, a multivariate database on tourism industry, information economy and regional development is constructed based on the Chinese provincial macro panel, and then the subsequent spatial autocorrelation test and spatial Dubin model estimation are carried out.

2.1 Description of study area and data sources

The empirical sample covers 30 Chinese provincial units observed annually from 2012 to 2022, forming a balanced panel for identifying temporal changes and cross-regional differences. This can not only reflect the spatial differences of the development level of digital economy more fully, but also help to depict the characteristics of tourism in different provinces and regions, such as spatial relations, geographic proximity and spillover characteristics. Therefore, the balanced panel sample established in this study can be expressed as follows.

$$\mathcal{D} = \{(y_{it}, \text{dig}_{it}, Z_{it}) \mid i = 1, 2, \dots, 30; t = 2012, 2013, \dots, 2022\} \quad (1)$$

where y_{it} represents the tourism spatial pattern index of region i at time t ; dig_{it} is the digital economy development level of the region; Z_{it} includes control variables such as the level of transportation infrastructure construction, urbanization rate, industrial structure and openness to the outside world. Using this definition, there are $30 \times 11 = 330$ observations.

Tourism-related variables are compiled from national and provincial statistical yearbooks, including tourism revenue, tourist arrivals and service capacity indicators. The basic data of the digital economy are mainly calculated by using the "China Statistical Yearbook", "China Informatization Development Report" and the Internet and communication industry data of various provinces and cities, and some open databases related to digital inclusive finance. Spatial relationship data are generated from provincial boundary adjacency and the geographic coordinates of provincial capitals, which are then used to construct contiguity and distance-based spatial weight matrices. Because the data from different sources are comparable, the monetary variables are deflated in fixed base years, and the actual values are as follows:

$$x_{it}^* = \frac{x_{it}}{P_t} \times 100 \quad (2)$$

Specifically, the price-corrected real value x_{it}^* and the original nominal value x_{it} are used to calculate the price index P_t with a base year of 100, where the missing values are replaced by the previous year. Continuous variables with large fluctuations are logarithmically transformed, and extreme observations are winsorized at the 1% and 99% levels to reduce the disturbance of outliers in spatial model estimation. According to the objectives of the research, the main research objects and their sources are shown in Table 2.

Table 2: Sample data composition and main sources

Data Category	Main Content	Specific Definition	Main Source
Tourism industry data	Tourism revenue, tourist arrivals, and tourism enterprise and service capacity information	Used to measure the scale of the tourism industry and its spatial distribution characteristics	China Tourism Statistical Yearbook, provincial statistical yearbooks
Digital economy data	Indicators related to digital infrastructure, Internet development, digital finance, and information services	Used to construct a composite indicator of digital economy development level	China Statistical Yearbook, digital economy development level statistical materials, public databases
Control variable data	Urbanization, transportation accessibility, industrial structure, fiscal support, external openness, etc.	Used to control for the effects of regional heterogeneity	China Regional Economic Statistical Yearbook, provincial statistical bulletins
Spatial data	Provincial adjacency relations, geographic center coordinates, and regional distance	Used to construct the spatial weight matrix	Standard administrative division maps, compiled geographic coordinate data

2.2 Construction of indicator system for measuring the development level of digital economy

Digital economy development is a composite process involving infrastructure availability, digital industry activity, industrial digital penetration and application environment rather than a single observable variable. If one or several of the above indicators, such as the number of Internet access, the scale of mobile communication users, and digital finance, are directly replaced, the evaluation results may be too biased and cannot objectively reflect the gradient difference of digital economy development between regions. Therefore, based on the availability of provincial data, index representation and tourism relevance, this study constructs a relatively complete high-quality development measurement index system of digital economy around the dimensions of digital basic support, digital business operation ability, industrial deep integration development level and digital technology application. The entropy weight method is adopted to assign data-driven weights, so that indicators with stronger regional variation contribute more to the composite digital economy index.

In the process of index processing, considering that different index dimensions and value directions are not consistent, dimensionless standardization is performed on the original data. For positive indicators, Equation (3) is used to process:

$$z_{ij} = \frac{x_{ij} - \min(x_j)}{\max(x_j) - \min(x_j)} \quad (3)$$

For the reverse index, Equation (4) is used to process:

$$z_{ij} = \frac{\max(x_j) - x_{ij}}{\max(x_j) - \min(x_j)} \quad (4)$$

Here, x_{ij} represents the original value of the j -th indicator in the i th region, and z_{ij} represents the normalized result. After standardization, the proportion of each index in the sample was further calculated:

$$p_{ij} = \frac{z_{ij}}{\sum_{i=1}^n z_{ij}} \quad (5)$$

On this basis, the information entropy e_j and the difference coefficient d_j of the j -th indicator are calculated. An indicator receives a larger weight when its values show stronger dispersion across provinces, because such dispersion contains more information for distinguishing digital economy levels. The weight of each index and the composite index are calculated as follows:

$$w_j = \frac{d_j}{\sum_{j=1}^m d_j}, \quad DE_i = \sum_{j=1}^m w_j z_{ij} \quad (6)$$

where w_j represents the weight of the j -th indicator; DE_i represents the overall and coordinated development level of the digital economy in region i . This method can effectively retain the variation information in the sample, and the measure value can better reflect the actual situation of digital economy development between regions.

For this study, the digital economy index is designed to reflect both general digital development and its potential connection with tourism spatial organization. Digital infrastructure describes the availability of network access and information transmission; digital industry development reflects the supply of software, communication and information services; industrial digitalization measures the penetration of digital tools into service sectors; and the digital application environment captures digital finance, innovation investment and market usage. These dimensions allow the index to distinguish provincial digital levels and provide a basis for later grouped comparison. As shown in Figure 1, the constructed evaluation model of digital economy development degree includes three levels: target level, dimension level and indicator level, and points to the same direction -- measuring and comparing the overall digital economy economic development degree of different regions.

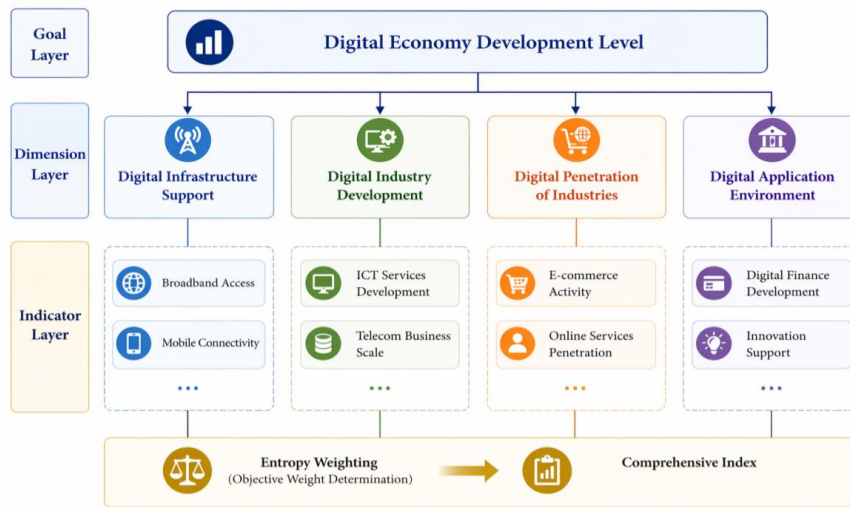


Figure 1: Framework of indicator system for measuring the development level of digital economy

2.3 Design of measurement method for spatial distribution of tourism industry

Tourism spatial distribution cannot be adequately described by tourism revenue or visitor arrivals alone, because regional tourism concentration also depends on specialization degree, land-based carrying density and national market share. It is easy to confuse the industry scale with the spatial organization and cannot accurately distinguish the aggregation characteristics of each regional system of tourism if the spatial pattern is only represented by the total income of tourism or the amount of tourist reception. In this study, the triple coupling measurement method of "relative concentration-spatial density-occupancy ratio" is used to construct the spatial distribution index of the tourism industry that can be applied to the subsequent spatial statistical model. The specific process is shown in Figure 2.



Figure 2: Design framework of spatial distribution measure method for tourism industry

Location quotient is introduced to capture whether tourism occupies a stronger position in a province than it does in the national economic structure. The higher the value of location entropy, the greater the proportion of tourism in the local economy of the region, the more significant the tourism function. The formula is as follows.

$$LQ_{it} = \frac{T_{it}/GDP_{it}}{\sum_{i=1}^n T_{it} / \sum_{i=1}^n GDP_{it}} \quad (7)$$

where LQ_{it} represents the geographic agglomeration level of tourism in region i in year t , T_{it} represents the scale of tourism, which is represented by tourism income in this study. GDP_{it} stands for regional GDP. When $LQ_{it} > 1$, it indicates that the relative concentration level of tourism is higher than the national average.

The analysis of location entropy cannot fully reflect the development of tourism industry. In some regions, although the proportion of tourism industry in the local industrial structure is

large, the large area of the local area does not mean that the spatial agglomeration of the tourism industry is high. To complement the specialization measure, tourism spatial density is calculated to reflect the tourism economic output carried by each unit of administrative land area.

$$DEN_{it} = \frac{T_{it}}{A_i} \quad (8)$$

where EN_{it} represents the spatial density of the tourism industry and A_i is the administrative unit. This index can describe the agglomeration of tourism development in regional space, and can better reflect the economic belt along the river, the core urban agglomeration and the tourism industry concentration area.

In addition, in order to avoid the masking effect of relative index on the difference of absolute status, the tourism industry share index is also introduced to identify the status of each region in the national tourism industry structure. Its expression is:

$$MS_{it} = \frac{T_{it}}{\sum_{i=1}^n T_{it}} \quad (9)$$

Among them, MS_{it} is the proportion of tourism industry in region i to the whole country. The index can reflect its contribution to the whole national system, and to a certain extent, it realizes the global consideration of spatial measures, rather than just the comparison results relative to a certain region.

In view of the differences in dimension and magnitude of the three types of indicators, LQ'_{it} , DEN'_{it} and MS'_{it} are standardized to establish the comprehensive evaluation index of tourism spatial pattern:

$$TSD_{it} = \frac{LQ'_{it} + DEN'_{it} + MS'_{it}}{3} \quad (10)$$

Among them, TSD_{it} represents the degree of tourism spatial agglomeration in region i , which is the result of normalizing LQ'_{it} , DEN'_{it} and MS'_{it} ; The larger the value of this index, the higher the degree of specialization of regional tourism, the higher the degree of industrial agglomeration, and the stronger radiation ability in the domestic tourism market. In this way, the spatial pattern of tourism is not only a simple problem of size or proportion, but also a comprehensive indicator factor with relativity, location and integrity.

2.4 Spatial autocorrelation test and spatial weight matrix construction

After constructing the tourism spatial distribution index, the next step is to test whether provinces with similar tourism concentration tend to cluster or disperse in geographic space. If the spatial distribution of tourism in each region is independent of each other, the general panel regression method can be used to complete the preliminary estimation. However, when the tourism of adjacent areas has the characteristics of agglomeration, diffusion or interactive evolution, it needs to be confirmed by spatial statistics. Tourism activities are not independent operation of a certain area, tourist flow, network marketing, transportation accessibility, resource sharing and location competition may make the tourism change in one area and spread to the surrounding area. Therefore, on the basis of exploring the heterogeneity of tourism geographical pattern under different digital stages, it is necessary to test its spatial correlation, and on this basis, construct a spatial weight matrix that can reflect the interaction between regions.

In this study, the global Moran's I index is used to analyze and test the spatial distribution and overall spatial correlation of the tourism industry, and the calculation formula is as follows:

$$I = \frac{n}{S_0} \cdot \frac{\sum_{i=1}^n \sum_{j=1}^n w_{ij} (TSD_i - \bar{TSD})(TSD_j - \bar{TSD})}{\sum_{i=1}^n (TSD_i - \bar{TSD})^2} \quad (11)$$

where n represents the number of units, TSD_i and TSD_j represent the tourism spatial pattern index of unit i and its neighbor j , respectively. TSD is the overall data mean, w_{ij} is the distance weight factor between two connected units, that is, the correlation coefficient between adjacent units. Finally, the spatial distribution of tourism industry between regions can be obtained by calculating $S_0 = \sum_i \sum_j w_{ij}$. A positive Moran's I indicates that provinces with similar tourism spatial distribution values are geographically clustered. A negative value suggests spatial mismatch between neighboring units, while a value near zero implies weak spatial dependence.

In order to better explore the spatial organization in the region, the local Moran's I index is used to divide the degree of agglomeration into high agglomeration area, low agglomeration area and high and low interval area, and the calculation formula is as follows:

$$I_i = \frac{(TSD_i - \bar{TSD})}{m_2} \sum_{j=1}^n w_{ij} (TSD_j - \bar{TSD}) \quad (12)$$

where I_i represents the local spatial correlation value in the i th region; $m_2 = \frac{1}{n} \sum_{i=1}^n (TSD_i - \bar{TSD})^2$. The index can decompose the overall regional spatial connection into each point, facilitate the analysis of hot spots, cold spots and their connectivity in the tourism spatial pattern, and provide a basis for interpreting the differential diffusion between developed and underdeveloped areas of digital economy.

The identification of spatial dependence is sensitive to how interprovincial links are defined; therefore, the study constructs both contiguity-based and distance-based spatial weight matrices. The latter is a mathematical expression to express the spatial relationship between different location units, and the choice of this expression directly affects the understanding of its spatial effect. Due to the constraints of geographical proximity and spatial distance between tourist destinations in China, two different weight matrices are used in this study: one is the degree of connection between adjacent areas; The other category is the actual distance space. It is denoted as: adjacent weight matrix.

$$w_{ij}^{(1)} = \begin{cases} 1, & \text{If region } i \text{ has a common boundary with region } j \\ 0, & \text{Others} \end{cases} \quad (13)$$

This matrix is mainly for the analysis of spatial intersection, and can represent the state of direct spread of tourism factors to surrounding areas. In addition, the reciprocal matrix of geographic distance is constructed to avoid only considering the adjacent relationship and ignoring the interaction between non-adjacent but relatively close regions.

$$w_{ij}^{(2)} = \begin{cases} \frac{1}{d_{ij}}, & i \neq j \\ 0, & i = j \end{cases} \quad (14)$$

where, d_{ij} is the spherical distance between the provincial capital cities of region i and region j . The shorter the distance is, the greater the spatial influence is; otherwise, the weaker

the spatial influence is. To some extent, d_{ij} can better reflect the spatial attenuation characteristics of tourism flow, information flow and digital service flow. In order to facilitate the comparison of different types of matrices, the weight vector is normalized, namely:

$$W_{ij}^* = \frac{W_{ij}}{\sum_{j=1}^n W_{ij}} \quad (15)$$

Because the standardized result makes the weight size of each row equal and the sum is 1, it is helpful to understand the posterior spatial effect parameters and effectively reduce the estimation error caused by the unequal number of links between regions. On this basis, this study uses the adjacent weight matrix and also uses the geographic distance matrix to check the robustness, so as to improve the reliability of model recognition. According to this assumption, the process of spatial correlation test and weight matrix construction can be summarized as shown in Figure 3.

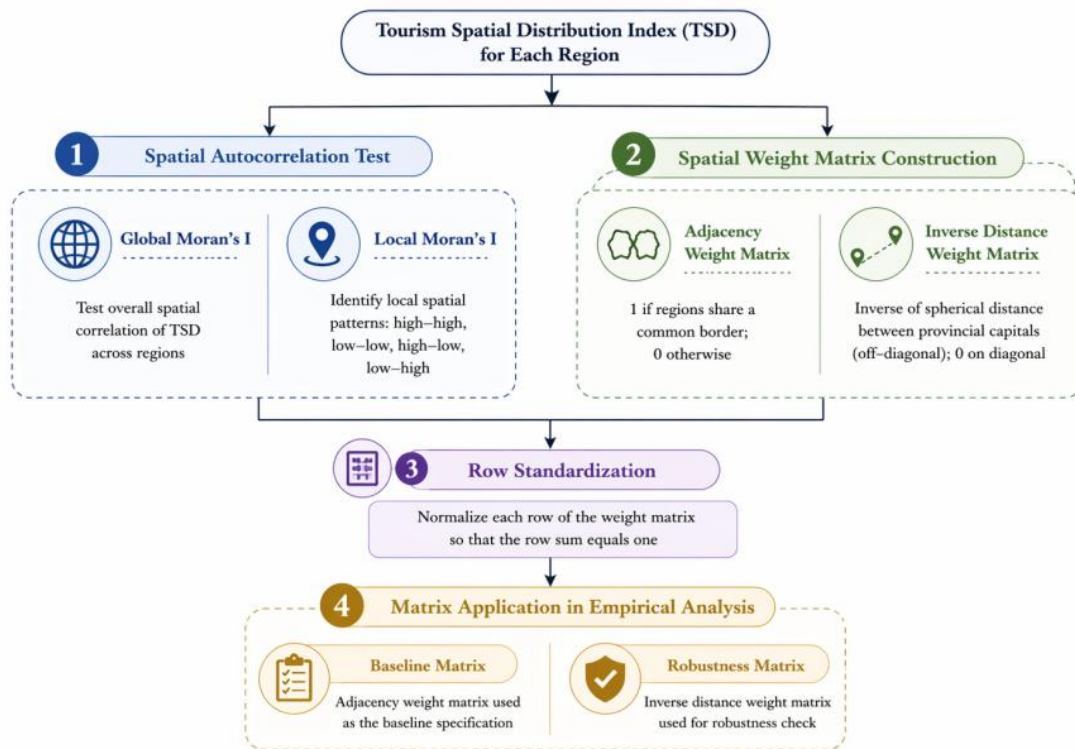


Figure 3: Process of spatial autocorrelation test and spatial weight matrix construction

2.5 Construction of multidimensional analysis model of differential effect of spatial distribution of tourism industry based on Spatial Dubin Model

After measuring tourism spatial distribution and digital economy development, the analysis turns to whether digital factors affect tourism concentration only within a province or also through neighboring provinces. When the geographical layout of tourism is affected by the digital economy, its scope of action is not limited to the local area, but may also spread to the surrounding area. Influenced by the development of digital infrastructure, the application of network platform, the acceleration of information circulation and other factors, it will lead to the change of tourism organization resources, and may affect the tourism development mode of the surrounding region through transportation coordination, market interaction, consumer

spillovers and other ways. A conventional panel model may ignore feedback between neighboring provinces. The spatial Dubin model is therefore used because it incorporates both the spatial lag of tourism distribution and the spatial lag of digital economy development.

In order to identify the heterogeneous characteristics of digital economy development at different stages, the study area is first divided into development stages according to the digital economy comprehensive indicator DE_i constructed above. Given the clear provincial gap in digital economy development, the sample is divided into low-, middle- and high-level groups according to the 33rd and 66th percentile thresholds of the composite digital economy index.

$$G_i = \begin{cases} 1, DE_i \leq Q_{33} \\ 2, Q_{33} < DE_i \leq Q_{66} \\ 3, DE_i > Q_{66} \end{cases} \quad (16)$$

where Q_{33} and Q_{66} represent the 33rd and 66th percentiles of the digital economy composite index, respectively. G_i represents the level of digital economy development of region i . In this way, regional differences will not be affected, and estimation based on this can avoid only using the average value as a predictor variable, and can investigate the spatial characteristics of tourism development under different levels of digital economy.

Accordingly, the following Spatial Dubin Model with two-way fixed effects is constructed:

$$\begin{aligned} TSD_{it} = & \rho \sum_{j=1}^n w_{ij} TSD_{jt} + \beta_1 DE_{it} + \beta_2 X_{it} + \\ & \theta_1 \sum_{j=1}^n w_{ij} DE_{jt} + \theta_2 \sum_{j=1}^n w_{ij} X_{jt} + \mu_i + \lambda_t + \varepsilon_{it} \end{aligned} \quad (17)$$

TSD_{it} represents the spatial distribution degree of tourism; Where ρ is the spatial lag coefficient; DE_{it} indicates the development level of digital economy; X_{it} is the control variable group of economic level, urbanization rate, transportation convenience, industrial structure and foreign trade liberalization. μ_i and λ_t denote the region fixed effect term and the time fixed effect term, respectively. Here, ε_{it} denotes the random disturbance term. In this formula, $\sum w_{ij} TSD_{jt}$ is used to represent the spatial lag influence of the tourism spatial pattern in the surrounding area on the region, and $\sum w_{ij} DE_{jt}$ is used to represent the spatial spillover influence of the digital economy development in the adjacent area on the tourism spatial pattern in the region.

Because spatial feedback causes the estimated coefficients to differ from marginal impacts, the model results are further decomposed into direct, indirect and total effects. The coefficient matrix of spatial effect on the core explanatory variable DE can be expressed as follows.

$$S(DE) = (I - \rho W)^{-1}(\beta_1 I + \theta_1 W) \quad (18)$$

where I represents the identity matrix and W is the matrix composed of spatial weights, the multivariate influence pattern of spatial effect of digital economy on tourism development can be obtained. When taking the average value of each element on the main diagonal of the matrix, the influence of local digital economy development on the spatial pattern of tourism in the region can be reflected. The non-main diagonal rows are averaged to represent their indirect effects on other regions. The sum of the two is the total effect. Direct and indirect effects can also be expressed as follows.

$$DEffect = \frac{1}{n} \text{tr}(S(DE)), IEffect = \frac{1}{n} 1'S(DE)1 - DEffect \quad (19)$$

where $\text{tr}(\cdot)$ denotes the trace of the matrix, and $\mathbf{1}$ is the column vector of ones. The advantage of this decomposition is that it can eliminate the interference caused by spatial feedback being treated as the influence of a single region, and more clearly depict the radius and degree of influence of digital economy on different levels of regions.

This section not only examines the influence intensity of digital economy on tourism spatial layout, but also focuses on whether its action mechanism is manifested as local endogenous strengthening or spatial transmission spreading to surrounding areas. At the same time, it is also hoped to explore that less developed regions are more driven by neighboring regions, and for regions that have developed to a higher level, they are more likely to spill out. Therefore, in the following empirical part, the Spatial Durbin Model will be used to estimate and compare different effects (direct effect, indirect effect and total effect) under different digital economy development levels by grouping, so as to reflect the diversity of influencing factors of tourism spatial evolution. The overall analysis process is shown in Figure 4.

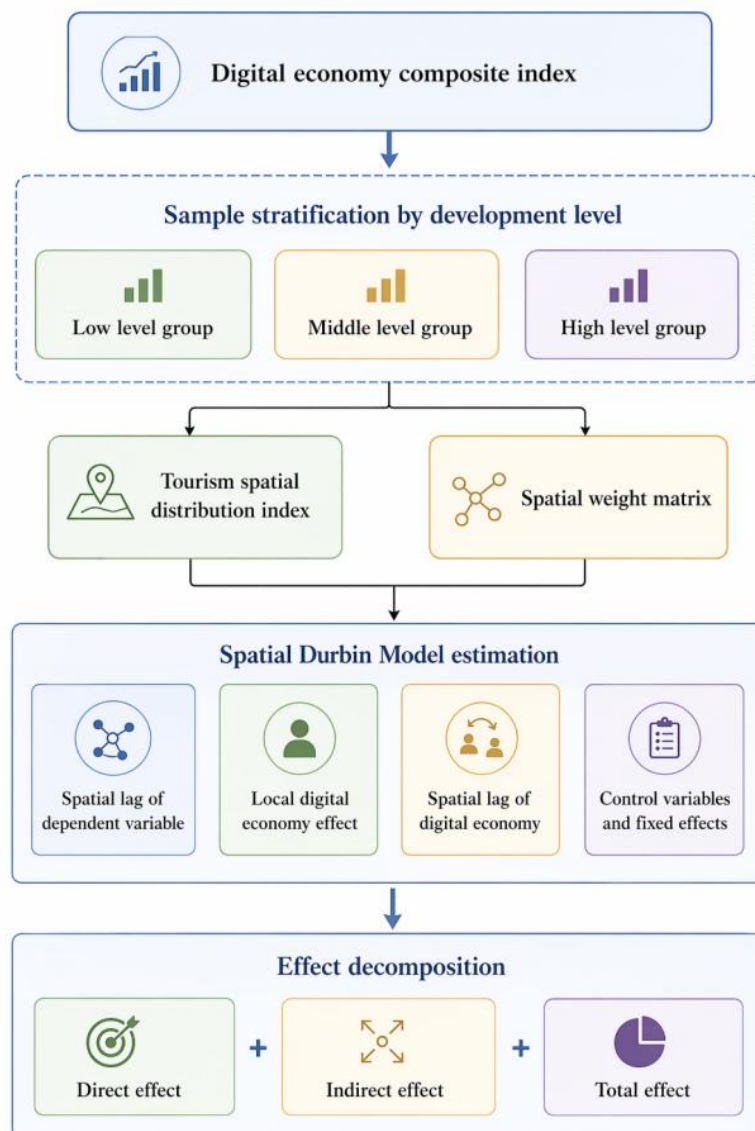


Figure 4: Framework of differential effects multidimensional analysis based on Spatial Durbin Model

3 Analysis of results

Using the composite digital economy index, the 30 provinces are grouped into low-, middle- and high-level categories, with 10 provinces in each group, to compare how tourism spatial distribution evolves under different digital conditions. On this basis, the characteristics of tourism industry development pattern are explored according to its development trend, difference degree and composition. On the one hand, this method is to measure the relative level of tourism development in different regions, and to find out the evolution law of tourism spatial organization under the level of economic development of digital economy, so as to provide a realistic basis for the subsequent estimation of the impact factor of the heterogeneity effect in the Spatial Dubin Model.

3.1 Analysis of spatial distribution characteristics of tourism industry under different levels of digital economy development

Table 3 shows the changes of the spatial distribution index of tourism industry in different digital economy development level groups in the sample years. This pattern indicates the average values of the three level groups in 2012 were 0.521, 0.358 and 0.247, respectively, and 0.714, 0.533 and 0.386 in 2022. Increases of 0.193, 0.175 and 0.139 in ten years. The low-level group records the highest growth rate, rising by 56.28%, compared with 48.88% in the middle-level group and 37.04% in the high-level group. This pattern suggests that regions with weaker digital foundations still have considerable room for tourism spatial upgrading once digital connectivity and service platforms begin to improve. However, if it is compared with reality, the grade difference between the three types of regions does not disappear, and the high-level group still has advantages.

Table 3: Changes in spatial distribution index of tourism industry under different levels of digital economy development

Group	2012	2015	2018	2022	Increase, 2012–2022	Growth Rate / %
Low-level group	0.247	0.272	0.319	0.386	0.139	56.28
Middle-level group	0.358	0.394	0.447	0.533	0.175	48.88
High-level group	0.521	0.569	0.629	0.714	0.193	37.04

From 2012 to 2019, the indicators of the three categories showed continuous growth, the tourism spatial pattern showed a trend of continuous optimization. Affected by external interference, there was a decline in 2020, but the decline was significantly different. The high range dropped from 0.651 in 2019 to 0.618 in 2020, with a decline of 5.07%, and the middle range was the same, in which the middle level group dropped from 0.468 to 0.441, with a decline of 5.77%. However, the decline in the low level group was even greater, from 0.337 to 0.321, a decline of 4.75%. The 2020 decline shows that external shocks weakened tourism concentration in all groups, while the subsequent recovery implies that digital tools may support route adjustment, online demand matching and service coordination during the rebuilding process. However, there are differences in the recovery and expansion paths of different levels of regions. High-order regions focus on strengthening existing advantages, and low-order and middle-order regions are more likely to supplement and expand the key links of development.

Figure 5 presents a clear hierarchical trajectory: the high-level group remains at the top, the middle-level group accelerates after 2018, and the low-level group improves steadily but still stays below the other two groups. Among them, the distance between the high-level and

the low-level group was 0.274 in 2012, and the distance has expanded to 0.328 in 2022. The distance between high-level and medium grade will expand from 0.163 in 2012 to 0.181 in 2022. This widening gap suggests that digital economy may reinforce existing advantages in tourism specialization, spatial density and market share, especially in provinces with stronger digital foundations. The accelerated slope of the intermediate grade curve after 2018 indicates that it is in the transition stage from single point breakthrough to overall promotion. Although the low level shows a large improvement, this optimization is local and does not reach a stable and continuous peak propagation area.

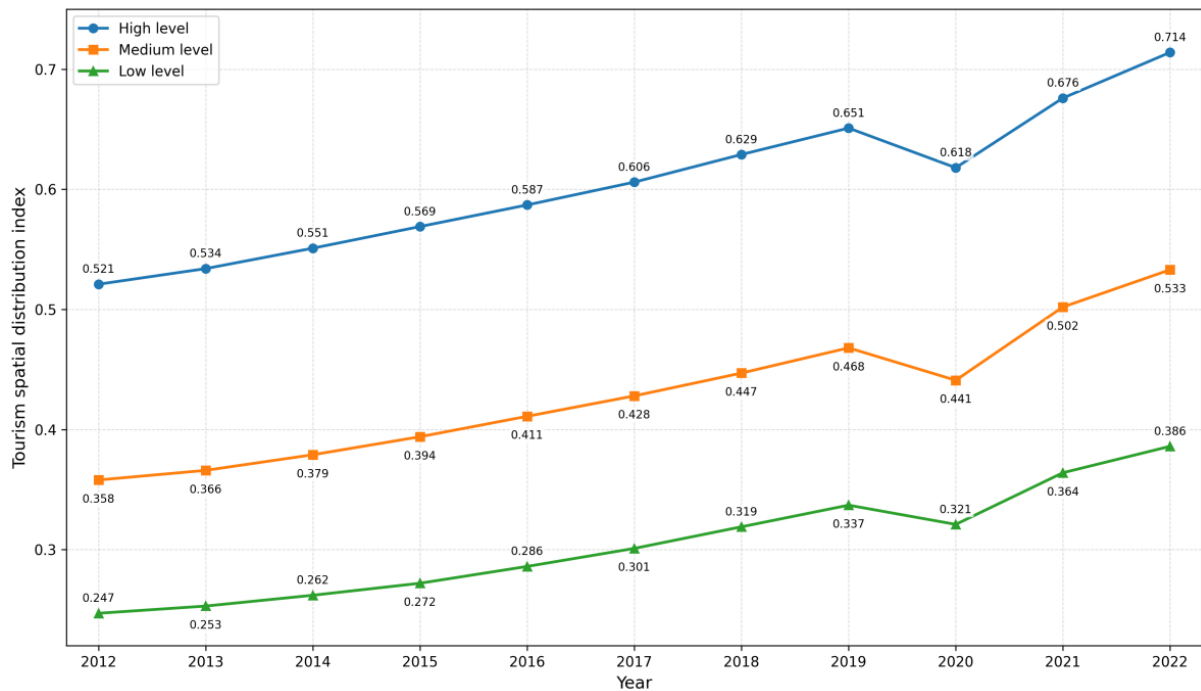


Figure 5: Change trend of spatial distribution index of tourism industry in different digital economy development level groups from 2012 to 2022

It is difficult to fully grasp the internal mechanism of difference formation by only examining the total index. In order to explore the internal mechanism in the process of difference formation, the three dimensions of the tourism location characteristic indicators of the three types of regions in 2022 were compared and analyzed (see Table 4). It was found that the level of tourism development in the high-level regions was relatively high in the three dimensions of agglomeration, spatial density and tourism industry share, where the standardized mean of location entropy was 0.70. The standardized mean of spatial density is 0.74, and the standardized mean of share is 0.70, this type of area not only accounts for a high proportion in the local economy, but also has a high carrying capacity per unit area, and is an important node of the domestic tourism network. The values of the three types of indicators in the middle level region are 0.52, 0.55 and 0.53, respectively, which are in the conversion process from high level to low level, and have obvious transition characteristics. However, the performance of the low-level group in these three dimensions is relatively weak, that is, the standardized mean value of location entropy is 0.41, the standardized mean value of spatial density is 0.37, and the standardized mean value of share is 0.38, which indicates that they still have low spatial capacity, low market share and low agglomeration degree.

Table 4: Comparison of dimensions of spatial distribution composition of tourism industry under different levels of digital economy development in 2022

Group	Mean Standardized Location Quotient	Mean Standardized Spatial Density	Mean Standardized Share	Intra-group Coefficient of Variation	Proportion of Provinces Above the National Mean / %
Low-level group	0.41	0.37	0.38	0.205	10.0
Middle-level group	0.52	0.55	0.53	0.173	40.0
High-level group	0.70	0.74	0.70	0.149	90.0

Table 4 also shows that there are differences in the degree of dispersion within each region. The intra-group variation coefficient of the high-level group is 0.149, which is lower than 0.173 of the medium-level group and 0.205 of the low-level group, but its mean value is higher than that of the other two groups, the high-level location is generally better, and the internal structure is more stable, and the spatial agglomeration pattern has been basically formed. Relatively speaking, the dispersion degree is the largest in the lowest level group, which means that some areas in the group will be higher than most areas, while other areas are in a state of low speed development. At the same time, it can also be seen that the number of provinces higher than the national average level is 90.0% in the high-level group, 40.0% in the intermediate group, and only 10.0% in the lowest level group, which also indicates that the higher the level of digital economy development, the regions can easily break through the general development cycle and enter the stable and rapid growth period.

3.2 Empirical analysis of differential effect of spatial distribution of tourism industry based on Spatial Dubin Model

After the measurement of the spatial distribution index and the test of spatial correlation of the tourism industry, this study further uses the two-way fixed effect Spatial Dubin Model to estimate the direction, strength and spatial transmission path of the digital economy's influence on the spatial distribution of the tourism industry. Model specification is supported by LM, LR, Wald and Hausman tests, which confirm the suitability of the two-way fixed-effect spatial Dubin model. The test results show that the spatial Dubin model can not be reduced to the spatial lag model or the spatial error model, where the Hausman statistic is 17.86 ($p=0.021$), so the two-way fixed effect spatial Dubin model is used to estimate. Based on this, the regression is performed on the overall sample, the low level group, the medium level group and the high level group of digital economy, respectively, and the estimation results are shown in Table 5.

Table 5: Estimation results of Spatial Dubin Model

Variable	Full Sample	Low-level Group	Middle-level Group	High-level Group
Digital economy development level (DE)	0.164*** (0.041)	0.087* (0.048)	0.143*** (0.039)	0.208*** (0.052)
Spatial lag of digital economy (W×DE)	0.091** (0.036)	0.126*** (0.041)	0.084** (0.034)	0.037 (0.029)
Spatial lag term (ρ)	0.287*** (0.074)	0.341*** (0.083)	0.296*** (0.078)	0.221** (0.091)
Economic development level	0.052** (0.024)	0.031 (0.027)	0.047* (0.025)	0.068** (0.031)
Urbanization level	0.073*** (0.021)	0.056** (0.024)	0.071*** (0.022)	0.082*** (0.026)
Transportation accessibility	0.041* (0.022)	0.034 (0.025)	0.046* (0.024)	0.038 (0.027)
Advanced industrial structure	0.028 (0.019)	0.021 (0.022)	0.033* (0.019)	0.026 (0.021)
Degree of opening-up	0.019 (0.016)	0.012 (0.018)	0.017 (0.016)	0.029* (0.017)
R ²	0.691	0.648	0.673	0.702
LogL	246.37	89.14	93.82	97.56

Note: *, denote significant at the 1%, 5% and 10% levels, respectively.

Table 5 reports a significant spatial lag coefficient of 0.287 for the full sample, which means that tourism spatial concentration is not confined to provincial boundaries. Tourist mobility, interprovincial transport links, industrial collaboration and information diffusion allow tourism development in one province to affect neighboring provinces. The estimated coefficient of digital economy development is 0.164. After controlling for economic development, urbanization, transport accessibility, industrial structure and openness, a one-unit increase in the digital economy index is associated with a 0.164 increase in tourism spatial agglomeration. In addition, it is found that the coefficient of spatial lag digital economy term is also positive (0.091) and significant at the 5% level, which indicates that the digital development of adjacent regions can also promote the spatial agglomeration of local tourism industry. It shows that the digital economy has obvious spillover effect characteristics.

However, the grouped regression results show that there is a hierarchical difference in this effect. For the low-level group, the local digital economy coefficient is 0.087, while the spatially lagged digital economy coefficient reaches 0.126. This result suggests that low-level regions depend more on external digital spillovers from nearby provinces than on their own digital foundations. In the middle-level group, the local coefficient and the spatial lag coefficient are 0.143 and 0.084, respectively. This group is therefore located in a transitional stage, where local digital accumulation and neighboring spillovers jointly support tourism spatial optimization. For the high-level group, the local coefficient increases to 0.208, whereas the spatial lag coefficient decreases to 0.037 and is not statistically significant. This indicates that tourism spatial optimization in digitally advanced regions is driven mainly by local infrastructure maturity, smart governance and platform integration rather than by external digital input.

In order to visually compare the changes of core variable coefficients in different groups, a comparison chart of core variable coefficients in different groups is drawn as shown in

Figure 6. Figure 6 shows a shift in the dominant driving force. As digital economy development rises, the local effect becomes stronger, while the neighboring spillover effect gradually weakens. This pattern reflects a transition from external dependence to mixed support and then to local self-reinforcement.

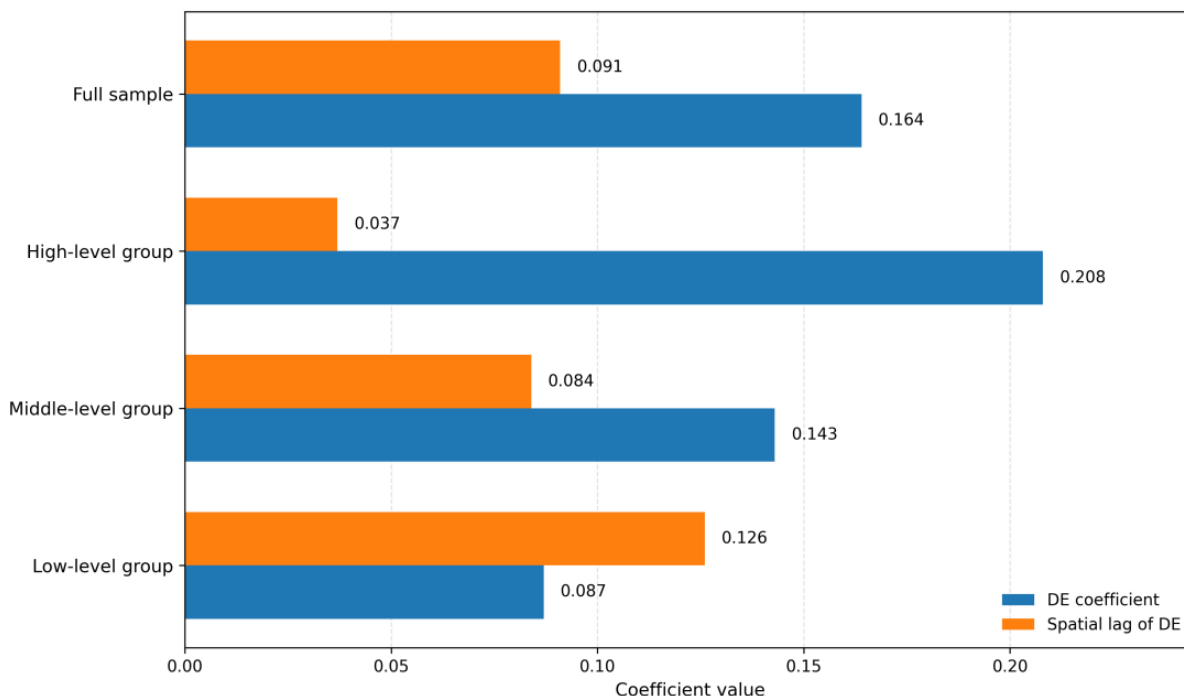


Figure 6: Comparison of coefficients of core explanatory variables for groups with different levels of digital economy development

Among the control variables, urbanization remains positively associated with tourism spatial distribution across all groups, with coefficients ranging from 0.056 to 0.082. This suggests that population concentration, public service supply and consumption space expansion provide basic support for tourism agglomeration. Economic development shows a positive effect in the full sample and in the middle- and high-level groups, suggesting that economically stronger provinces are better able to concentrate tourism resources and provide higher-quality services. Transportation accessibility is significant in the full sample and the middle-level group, indicating that tourism expansion at this stage still depends on the improvement of transport infrastructure. However, the significant positive effect of the degree of opening to the outside world is only reflected in the high level group, the regions with high digital level are more likely to convert the advantages of open business and trade into advantages of tourism development.

Because the spatial Dubin coefficient does not directly represent marginal impact, the digital economy variable is decomposed into direct, indirect and total effects. The full-sample direct, indirect and total effects are 0.172, 0.104 and 0.276, respectively. For the low-level group, the corresponding values are 0.096, 0.141 and 0.237; for the middle-level group, they are 0.154, 0.089 and 0.243; for the high-level group, they are 0.219, 0.035 and 0.254. This also verifies the change law of the above coefficients, that is, small-scale regions are more affected by neighboring regions, and large-scale regions rely more on their own information development to drive tourism space reconstruction.

In order to compare the proportion of direct and indirect effects between different groups, Figure 7 is drawn to reflect the proportion of direct and indirect effects in the whole effect. In

the low level group, the indirect effect accounted for 59.5% of the total effect, which was higher than the direct effect of 40.5%. In the medium level group, the proportion of direct effect increased to 63.4%; In the high level group, the direct effect accounted for 86.2%, and the indirect effect accounted for only 13.8%. This structure confirms that the mechanism of tourism spatial agglomeration changes with digital development level: low-level regions rely more on neighboring spillovers, whereas high-level regions depend mainly on local digital capacity. The small scale is to rely on the transmission power brought by the surrounding digital service enterprises, the radiation power of tourism information and the import of passenger flow to realize the improvement of its own space quality. The large-scale is a relatively stable tourism spatial agglomeration effect based on the local digital resource allocation ability, intelligent tourism management ability and comprehensive service ability.

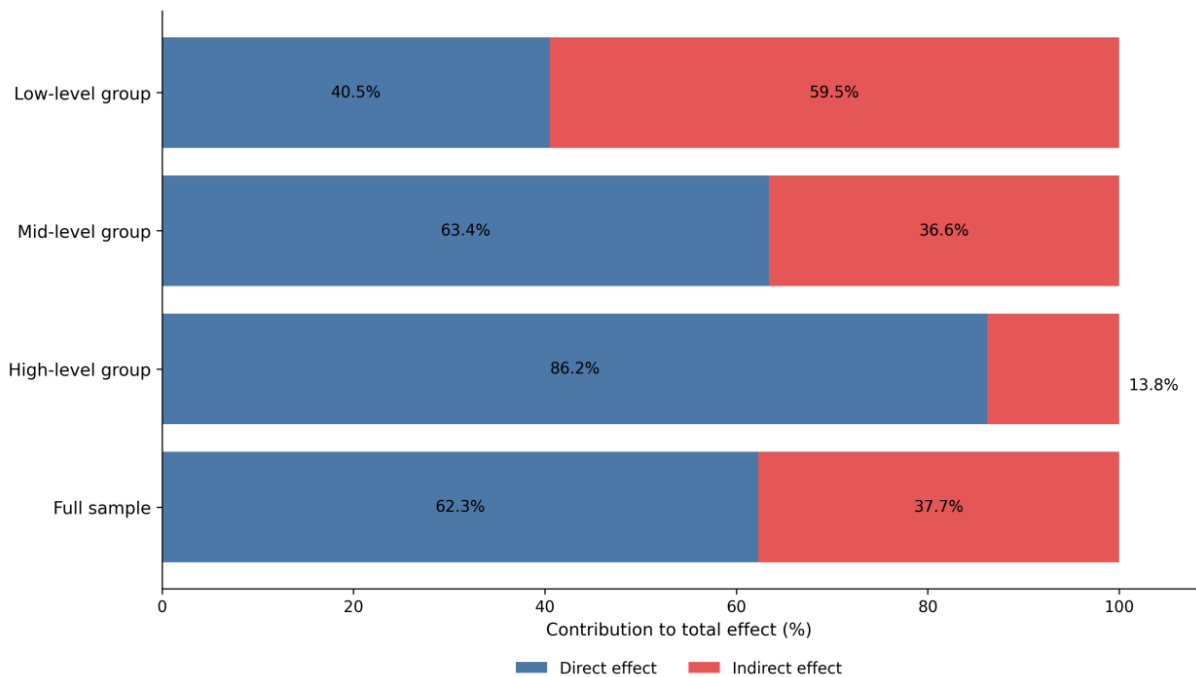


Figure 7: Group effect contribution structure of different levels of digital economy development

In summary, according to the results of the Spatial Dubin Model, the influence of digital economy development on the spatial distribution of tourism has significant spatial heterogeneity and hierarchical differences. On the whole, digitalization can improve the spatial governance ability of tourism industry development in the region, and promote the development of surrounding areas through spatial spillover effects. In the sub-sample, the low-level regions rely more on external digital empowerment, the medium-level regions pay equal attention to endogenous development and spatial expansion, and the high-level regions mainly play their own digital advantages to improve the tourism development model.

4 Discussion

The empirical results reveal that digital economy affects tourism spatial distribution through a stage-dependent transmission mechanism. The same digital factor does not generate identical spatial outcomes in low-, middle- and high-level regions. The results suggest that digital economy changes tourism spatial distribution through two channels: local digital capacity and

neighboring digital spillover. The balance between these two channels varies with the digital development level of each region. In other words, the change of tourism spatial form no longer completely depends on the resource advantage of single factor, but pays more attention to the interregional integration under digital superposition.

Groups with different levels of digital economy development showed the response characteristics of travel differentiation. Low-level regions show a larger indirect effect, which means that their tourism spatial upgrading is more closely related to digital service radiation, information diffusion and market connection from neighboring provinces. The high-level location shows stronger endogenous characteristics, when the digital infrastructure, platform ecology, and digital governance level accumulate to a certain height, the development of tourism space will be driven by external forces to endogenous expansion. This indicates that the development of digital economy at different levels will not act on all regions equally, but construct different transmission mechanisms and response degrees at different levels of the development stage.

The research method of this study has well identified the role and indirect impact of digital economy development on the spatial pattern of tourism, but there are still limitations. The provincial level can grasp the overall context, but it is difficult to reflect the differences between cities. Although the digital economy indicators of the basic support layer, development layer and application layer are selected as much as possible, some new platform behaviors and real-time dynamic attributes are not considered. Future research can further introduce city-scale samples, micro-tourism flow data and spatio-temporal variable weight method to identify the influence mechanism of digital economy on the evolution of tourism spatial pattern in a more detailed way.

5 Conclusion

This study verifies that the effect of digital economy on tourism spatial distribution is not uniform across regions. From 2012 to 2022, all three digital economy groups experienced an increase in tourism spatial distribution index, but the driving mechanism differed clearly by development level. On this basis, the spatial autocorrelation test is analyzed, and the Dubin model is used to empirically test the research hypothesis. The final results show that from 2012 to 2022, the spatial pattern index of the high, medium and low groups of tourism industry shows a growth trend. By 2022, the three groups of indices will be 0.714, 0.533 and 0.386, respectively. Compared with the increase rate from 2012 to 2022, the increase rate was 56.28% in the low level group, 48.88% in the medium level group, and 37.04% in the high level group. It shows that the development of digital economy makes the spatial pattern of tourism industry tend to be optimized. But this is not true in all regions. From the overall sample, the estimated coefficient of the development level of the digital economy is 0.164, and the coefficient of the spatial lag term is 0.287, the digital economy not only promotes the spatial agglomeration of the local tourism industry, but also has obvious spatial spilt effect. In the overall sample, the direct, indirect and total effects of digital economy are 0.172, 0.104 and 0.276, respectively. From the regional level, the indirect effect of low development level areas accounted for 59.5% of the overall force, and the direct effect of high development level areas accounted for 86.2% of the overall force, relatively underdeveloped areas relied more on exogenous digital empowerment, while developed areas relied more on endogenous digital ability to reconstruct tourism space. The findings suggest that policy design should be differentiated by digital development level. Low-level regions should strengthen interprovincial digital connectivity and platform access, middle-level regions should improve the conversion of digital spillovers into local tourism capacity, and high-level regions should

focus on smart governance, data integration and high-quality tourism service upgrading.

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