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Analysis on the Spatial Structure and Interaction of Aviation Network and Tourism Efficiency Network in Major Cities in China

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Abstract: Tourism efficiency is crucial for measuring sustainable tourism development. Examining the relationship between aviation and tourism efficiency networks is key to promoting their synergistic development in China's urban areas. This study employs various methods, such as complex network analysis method, entropy-weighted TOPSIS, tourism efficiency gravity model, and quadratic assignment procedure, to analyze the networks' spatial structure evolution characteristics and interaction effects. Results show that (1) China's major cities' aviation network has improved its organizational efficiency and formed a "double rhombus-single axis" spatial evolution pattern of the axis-spoke network. The number of intermediary networks and hub cities in the central and western regions has increased. (2) The tourism efficiency network adopts a "honeycomb" structure pattern with the simultaneous layout of "point-to-point" and "star" networks. The network's tourism efficiency follows "Pareto's Law," and tourism cities above the second level form a club group development. The tourism efficiency development potential area is shifting to the southwest. (3) The aviation and tourism efficiency networks exhibit a clear trend of synergistic evolution with a "path locking" phenomenon between them. Differences in tourism resource endowment, labor advantage, and capital advantage positively impact the aviation network's structure. Conversely, differences in revenue capacity and market scale negatively impact the structure. The aviation scale advantage, openness, intimacy, and influence exhibit decreasing positive effects on the tourism efficiency network's structure.

Keywords: Aviation Network; Tourism Efficiency Network; Spatial Structure Characteristics; Interaction Effects; China; Major Cities.

1. Introduction

China's air transportation industry is flourishing due to the government's encouragement of low-cost airlines and decreasing air travel costs. According to the Civil Aviation Administration of China, the country boasts 248 airports, 4,585 air routes, and an annual passenger volume of 440 million as of 2021. Air transportation services now reach 90% of the country's prefecture-level cities, 87% of the population, and 91% of the total economic volume. The relationship between air transportation and regional economic development is becoming increasingly intimate. In terms of tourists' air travel preferences, the Chinese Academy of Social Sciences' Tourism Research Center's "Research Report on the Trend of Travel Demand under the New Crown Pneumonia Epidemic" shows that after the epidemic, 44.2% of travelers chose air travel. Air transportation offers superior comfort, convenience, and safety, making it a popular choice for pre-tour transportation consumption. From the perspective of air passenger sources, according to Flight Manager's 2018 China Civil Aviation Passenger Development Trend Insight Report, Chinese people flew 610 million times in 2018, with 72% of them traveling to visit relatives. Air transportation contributes significantly to the tourism economy by facilitating intercity tourism through cross-regional high-speed network transmission channels [1]. It is a vital link for China's future tourism quality and efficiency. The overlap between air traffic systems and tourism efficiency demonstrates a spatial spillover, indicating China's transition towards high-quality tourism development. Tourism efficiency is a key factor in sustainable tourism development, and exploring the relationship between the aviation network and tourism efficiency network will promote the synergistic development of urban aviation and tourism in China.

The existing research on air traffic and tourism location advantage primarily considers the level of tourism development, overlooking the relationship between urban tourism sustainability and location advantage optimization. As a result, the impact of associated spatial networks on location advantage and the internal network structure of cities is often neglected [2]. To address this gap, this study combines "flow space theory" with complex network science to develop a new location advantage measurement, which assesses linkage strength, openness, and transit using complex network theory [3]. Myrdal's regional economic disequilibrium theory suggests that urban economic development disparities are unavoidable, highlighting the importance of coordinated development to serve the overall interests of cities [4]. Therefore, this study aims to explore the interactive influence of the spatial structure of aviation and tourism efficiency networks. Specifically, it seeks to answer three questions: 1) What is the law governing the evolution of the spatial structure of the aviation and tourism efficiency networks? 2) How does the aviation network impact the optimization of the tourism efficiency network? 3) What is the effect of unbalanced network element differences of aviation and tourism efficiency on the overall network spatial structure? The findings of this study offer theoretical contributions and scientific references to enhance the coordinated and sustainable development of cross-level networks. The study uses complex network analysis method, entropy-weighted TOPSIS method, Super-SBM model, tourism efficiency gravity model, and quadratic assignment procedure to reveal the spatial structure evolution characteristics of the aviation and tourism efficiency networks in major Chinese cities in 2010, 2015 and 2019. Empirical analysis is conducted to examine the "network-network" interaction. Finally, based on the study's findings and the current situation in China, recommendations are provided to promote the sustainable development of air traffic and tourism.

The contribution of this study is summarized as follows:

(1) The analysis of China's aviation network and tourism efficiency network is visualized and studied at a spatial level using the "flow space" complex network perspective, expanding the research on the relationship between the two.

(2) A network level index system is developed using complex network analysis to determine the dominance of Chinese cities' aviation networks, and spatial visualization analysis of the cities' aviation dominance and tourism efficiency is conducted.

(3) A non-parametric test method is introduced to measure the "network-network" interaction, providing additional research methods for aviation and tourism at the network level.

2. Literature Review

2.1. The impact of air traffic on tourism development

Academic inquiries into the impact of air traffic on tourism development have honed in on several key factors, including tourism passenger flows [5-14], tourism revenues [15-19], tourism demand intentions [20-23], and tourism spatial structure [24-26]. It is evident that there exists a strong interdependence between aviation and tourism flows, and as such, many studies have investigated the various elements that affect air passenger traffic, such as low-cost discount fares [5], liberal aviation policies [6], quality airline services [7], and stable flight capacity [8,12-13]. In one such study, Zhou et al. (2016) [9] delved into the air and rail accessibility of inbound tourism cities in China, and discovered that developed tourism cities are significantly impacted by air passenger flows in the short term. Yang et al. (2019) [10] built on this research to conclude that this passenger flow impact reaches its zenith at 1800-2000 km. Furthermore, Mazzola et al. (2022) [11] empirically measured the impact of air transport capacity on tourism flows in European countries from rapid growth to stable contribution through an econometric model. At the tourism revenue level, Forsyth (2006) [15] determined that the upfront costs of implementing air freedom policies in Australia are significantly higher than the tourism benefits. Similarly, Balsalobre-Lorente et al. (2021) [16] discovered a long-term asymmetric relationship between the impact of the completion of air transport on local tourism revenues in Spain. At the level of tourism demand intentions, Li (2016) [20] unearthed interdependence and complementarity between airline demand and tourism demand in Australia and the United States through simulation analysis. Furthermore, a previous study by Chung (2011) [21] found that air freedom policy had no bearing on the seasonality of tourism demand, but Wu et al. (2018) [22] found that regular chartered air travel across the Taiwan Strait in China weakened the instability of tourism demand. Finally, at the level of tourism spatial structure, air transportation has the capacity to break the spatial barrier of destination tourism markets and optimize the spatial structure of tourism sources [24]. In fact, Tian et al. (2022) [25] observed that the spatial spillover effect of air transportation was much higher than other transportation modes, as evidenced by a comparison of the spatial spillover effect of three modes of transportation on tourism economic growth in China: high-speed rail, road and air.

2.2. The impact of tourism on air traffic development

Numerous studies have been conducted to understand the influence of tourism on the development of air traffic, with a focus on various factors such as air passenger flow and demand [27-28], airport efficiency [29-30], spatial layout of airports and routes [31], and environmental pollution [32]. Among these studies, Ji et al. (2021) [27] employed the PVAR model and confirmed that the growth of domestic tourism passenger flow in China can contribute indirectly to the civil aviation industry in the long run. Law et al. (2022) [28] analyzed the relationship between inbound tourism and air passenger transport growth in CLMV countries and discovered that inbound tourism has a significant impact on air transport demand over the long term but not in the short term. Moreover, studies have also explored the impact of tourism on airport efficiency. Pavlyuk (2016) [29] found that the heterogeneity of tourism revenues and traffic at European airports has a significant impact on local airport layout and efficiency improvements. Fernandez et al. (2018) [30] found that tourism-oriented airports in Spain are more efficient than non-tourist airports. Additionally, airports with a predominantly free-travel share have demonstrated to be more efficient than those with a predominantly charter share. In terms of airport and route layout impacts, Ji et al. (2017) [31] revealed that differences in tourism development levels among cities in Yunnan Province, China, have a direct and significant impact on airport layout and construction, route capacity, number of flights, and route connections. These factors, in turn, determine the spatial pattern of the regional aviation network. Saenz-de-Miera (2014) [32] also explored the issue of tourism's impact on the environment and found that an increase in the number of tourists has directly led to more environmental pollution from air traffic in Mallorca, Spain. As a result, it is crucial to pay attention to the carbon emissions of tourist traffic to mitigate the environmental impact.

In the field of aviation and tourism, scholars have extensively researched the relationship between the two, covering various aspects such as passenger demand, airport layout, tourism revenue, industry policies, and environmental pollution. Through their studies, it has been shown that aviation has a significant impact on tourism income and passenger flow. However, there is still a gap in research regarding the influence of regions with aviation advantages on tourism efficiency networks. Similarly, while it has been established that tourism greatly impacts airport and route layouts, the effect of core elements of tourism on urban aviation networks requires further investigation. To address these gaps, this study will take the spatial structure characteristics of the two related networks as a starting point. Using a secondary assignment procedure, the interactive effects of the aviation and tourism networks will be explored, providing valuable insights for achieving high-quality, synergistic, and sustainable development of China's aviation and tourism networks. By shedding light on the relationship between these two networks, this study will pave the way for the creation of effective policies and strategies that will contribute to the growth of both industries.

3. Materials and Methods

3.1. Methods

3.1.1. Complex network analysis method

3.1.1.1. Overall network topology characteristics indicators

To scrutinize and analyze the compactness of the overall aviation network, this study employs the clustering coefficient measure [33]. The chosen formula for the specific index is expressed as follows:

$$C_i = \frac{2Z_i}{k_i(k_i-1)} \tag{1}$$

$$C = \frac{1}{n}\sum_{i=1}^{n} C_i \tag{2}$$

where Z_i represents the number of routes between the city points that have real air connections with city point i, and $2/k_i(k_i-1)$ represents the theoretical number of routes that could be formed by k_i city points with air connections to city point i. The average value of the ratio of the actual number of routes to the theoretical number of routes is represented by C. A higher value of C signifies a higher degree of connectivity among cities in the network, indicating a lesser dependence on a few cities.

To gain a deeper understanding of the circulation efficiency of the aviation network, we have opted to utilize the average path length measure to assess the overall aviation network, as highlighted in this study [33]. The chosen formula for the specific index is expressed as follows:

$$L = \frac{2}{n(n-1)}\sum_{i \geq j} d_{ij} \tag{3}$$

where L is the mean diameter distance between any two city points within the aviation network, and d_{ij} represents the minimum number of routes required for city point i to reach city point j. The lower the value of L, the greater the efficiency of the aviation network's connectivity.

3.1.1.2. Aviation network dominance index system

Based on widely used indicators for evaluating the benefits of urban aviation complex networks [33-36], we employ four indices to assess the extent of aviation network advantages (Table 1.). Specifically, we utilized degree centrality to characterize the magnitude of total city passenger traffic (aviation scale advantage), intermediary centrality to denote the level of control exerted by city points over their respective route network passenger traffic (aviation openness power), proximity centrality to measure the similarity of passenger traffic between cities (aviation intimacy power), and characteristic vector centrality to gauge the external long-term influence of city passenger traffic (aviation influence).

Table 1. Aviation network dominance index system

Target Level	Indicator Level	Formula	Formula Description
Aviation network dominance index system	degree centrality	$C_D(n_i) = \frac{d(n_i)}{n-1}$	$C_D(n_i)$ represents the centrality of city point *i*, indicating the higher position of city point *i* in the overall network; $d(n_i)$ represents the total air passenger traffic of city point *i*; *n* represents the number of all city points.
	intermediary centrality	$C_B(n_i) = \frac{2\sum_j^n \sum_k^n y_{jk}(i)/y_{jk}}{(n-1)(n-2)}$ $(j \neq k \neq i 且 j < k)$	A larger value of $C_B(n_i)$ represents a greater degree of control of total air passenger traffic at city point *i*. $y_{jk}(i)$ indicates the existence of total air passenger traffic passing through city point *i* between city points *j* and *k*. y_{jk} indicates the total air passenger traffic between city points *j* and *k*.
	proximity centrality	$C_c(n_i) = \frac{n-1}{\sum_{j=1}^n d_{ij}}$	Larger values of $C_c(n_i)$ represent smaller total air passenger traffic at city point *i* and closer to other city points; d_{ij} denotes the amount of direct air passenger traffic between city points *i* and *j*.
	characteristic vector centrality	$EC(i) = x_i = c\sum_{j=1}^{n} a_{ij}x_j$ $x = [x_1, x_2, x_3, \ldots, x_n]^T$ $x = cAx$ $Ax = \lambda x$	The larger the value of $EC(i)$, the greater the long-term influence of city point *i*; where x_i is the importance measure of node *i*, *c* is a proportionality constant, and *x* is the eigenvector of the eigenvalue c^{-1} of the aerial network matrix A.

3.1.2. Entropy-weighted TOPSIS method

This study adopts the entropy-weighted TOPSIS method to measure the dominance of urban aviation network. The method is based on the principle of comprehensive ranking, which involves measuring the Euclidean distance of positive and negative ideal solutions. It offers several advantages, such as small information bias, clear geometric interpretation, high computational flexibility, and wide applicability, with no rigid requirement on the sample size [37]. The specific steps of this approach in this study are outlined as follows [37-38]:

(1) Entropy method for weighting

To obtain the weights of the four indicators, the original data underwent a dimensionless normalization, followed by the application of the entropy value method. The entropy method determines the indicator weights based on the degree of difference reflected by the magnitude of the entropy value of various indicator information. As this method is well-established, it is not described in detail here, and we refer to the literature for the specific steps [39].

(2) Multiplying the standardized indicator matrix with the weight matrix determined by the entropy value method, the weighted standardized matrix X:

$$X = \begin{bmatrix} x_{11} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mn} \end{bmatrix} = \begin{bmatrix} r_{11}\varphi_1 & \cdots & r_{1n}\varphi_n \\ \vdots & \ddots & \vdots \\ r_{m1}\varphi_1 & \cdots & r_{mn}\varphi_n \end{bmatrix} \quad (4)$$

(3) Determining positive and negative ideal solutions:

$$X^+ = \max\{(x_{ij}|i = 1,2,\ldots,m)\}(j = 1,2,\ldots,n) = \{X_1^+, X_2^+, \ldots, X_n^+\}$$
$$X^- = \max\{(x_{ij}|i = 1,2,\ldots,m)\}(j = 1,2,\ldots,n) = \{X_1^-, X_2^-, \ldots, X_n^-\} \quad (5)$$

where X^+ represents the positive ideal solution, indicating the maximum value of the jth indicator in year i, while X^- represents the negative ideal solution, indicating the minimum value of the jth indicator in year i.

(4) The Euclidean distance of positive and negative ideal solutions was calculated for each index:

$$D_j^+ = \sqrt{\sum_{i=1}^{m}(x_j^+ - x_{ij})^2}\ ;\ D_j^- = \sqrt{\sum_{i=1}^{m}(x_j^- - x_{ij})^2} \quad (6)$$

(5) Calculating proximity:

$$C_j = \frac{D^-}{D^+ + D^-} \quad (7)$$

where the value of C_j takes the range of [0,1], and the larger the value of C_j, the smaller the gap between the evaluated city and the ideal solution, the higher the city aviation network dominance.

3.1.3. Super-SBM model

Previous studies on urban tourism efficiency have mostly used data envelopment models (DEA). However, the traditional DEA model can only measure efficiency values up to 1, making it difficult to effectively rank urban points and neglecting the impact of slack variables on efficiency measures [40]. In contrast, the Super-SBM model considers slack variables and fully measures the previously unmeasurable efficiency value of spillover effects of urban points. This model allows for efficiency values greater than 1 and enables a more robust measurement of urban tourism efficiency. The formula for the Super-SBM model is as follows:

$$\min\rho = \frac{1 + \frac{1}{m}\sum_{i=1}^{m} s_i^- / x_{ik}}{1 - \frac{1}{q}\sum_{r=1}^{q} s_i^+ / y_{rk}} \quad (8)$$

$$\text{s.t.}\begin{cases} x_{ik} \geq \sum_{j=1,j\neq k}^{n} x_{ij}\lambda_j - s_i^- \\ y_{rk} \geq \sum_{j=1,j\neq k}^{n} y_{rj}\lambda_j + s_r^+ \\ \lambda, s_i^-, s_r^+ \geq 0 \\ i = 1,2,\ldots,m; r = 1,2.\ldots,q; \\ j = 1,2,\ldots,n; j \neq k \end{cases} \quad (9)$$

where ρ is the tourism economic efficiency value, m and s are the number of input and output indicators respectively, s_i^- and s_i^+ are the slack of input and output respectively, and λ_j is the weight vector matrix. When $\rho \geq 1$, it means that the decision unit is effective; when $0 \leq \rho < 1$, it indicates that the decision unit is weakly effective and needs to improve the ratio of inputs and outputs to improve tourism economic efficiency.

Following the studies of existing scholars [40-42], this research considers the cross-attributes of the tourism industry and data availability, and selects the number of A-class scenic spots, the number of employees in accommodation and catering above the quota, and the number of travel agencies in each city as resource input factors (i.e., tourism resource endowment), labor input factors (i.e., tourism labor advantage), and capital input factors (i.e., tourism capital advantage), respectively. The total tourism revenue (i.e., tourism revenue capacity) and the total number of tourist arrivals (i.e., tourism market scale) of each city are chosen as output evaluation indicators.

3.1.4. Tourism efficiency gravity model

The gravitational force model is a reliable tool for assessing the tourism economic ties among regions, indicating the tourism economic radiation capacity of core city points to their neighboring counterparts and the absorption level of the latter to the influence of the former. In this context, the optimal synergistic combination of each tourism factor and regional economy in spatial location defines the urban tourism development process [43]. However, the conventional tourism gravitational model uses only total tourism revenue, number of A-class scenic spots, total tourist arrivals, and distance as formula variables [44-45]. Consequently, it fails to provide a comprehensive tourism efficiency analysis of cities from the input-output perspective of each factor, and the measurement results do not fully reflect the interaction relationship between tourism efficiency development and economic development. To address this limitation, the present study constructs a modified tourism efficiency gravity model and its matrix network by selecting the GDP of each city as well as tourism efficiency as variables based on Wang et al.'s (2017) [45] approach. The formula for the model is as follows:

$$Y_{ij} = \frac{\sqrt{E_i G_i}\sqrt{E_j G_j}}{D_{ij}^2} \quad (10)$$

where the tourism efficiency gravitational strength, denoted by Y_{ij}, is determined by the tourism efficiency values, E_i and E_j, of city points i and j, respectively. The GDP values, G_i and G_j, of these city points also factor into the equation. Additionally, the Euclidean distance between city points i and j, represented by D_{ij}, is taken into account.

3.1.5. Quadratic assignment procedure

The quadratic assignment procedure (QAP) is a nonparametric method that examines correlations among matrix network values. Unlike traditional parametric tests, QAP does not require the assumption of mutual independence among independent variables, making it more robust. It can also be applied to regression analysis of matrices and examine interaction effects between multiple networks [45]. The method has been shown to be robust and reliable by several scholars [46-47], avoiding issues of multiple collinearities of independent variables in causality analysis.

To further examine the interaction between the aviation network and the tourism efficiency network, we referred to previous studies on network interaction [45,48] and converted the sub-indicators of tourism efficiency and aviation network dominance into a matrix of difference relationships. This involves calculating the difference between city pairs of each sub-indicator based on the route relationship, and constructing a "network-net" mechanism of action. Firstly, the tourism efficiency network (TEN) is used as the dependent variable, while the four sub-networks of aviation scale advantage difference (ASA), aviation openness power difference (AOP), aviation intimacy power difference (AIP), and aviation influence difference (AI) serve as the independent variables. Secondly, the aviation network (AN) is used as the dependent variable, while the differences in tourism resource endowment (TRE), tourism labor advantage difference (TLA), tourism capital advantage difference (TCA), tourism revenue capacity difference (TRC), and tourism market size difference (TMS) are used as the independent variables. Thirdly, we make the tourism efficiency network (TEN) the dependent variable and the aviation network (AN) the independent variable.

3.2. Data sources

The map presented in this study is based on the standard map (review number: GS(2020)4619, scale: 1:48 million) provided by the Ministry of Natural Resources of China's standard map service website. The aviation network data was sourced from the "Civil Aviation from Statistics" report prepared by the Department of Development Planning of the Civil Aviation Administration of China. To maintain consistency, the major route classification criteria of the latest year (2019) was used as the guideline for selecting major city points. Routes and city points with traveler traffic exceeding 300,000 between 2010 and 2019 were chosen as the fundamental correlation data. VariFlight, OAG, and OpenFlight, which are professional aviation data platforms, were used to validate the data. Tourism efficiency network data and other indicators were collected from various sources including CEIC China Economic Database, China City Statistical Yearbook, and National Economic and Social Development Statistical Bulletin. The visualization levels corresponding to the classification from high to low were assigned levels 1 through 5.

4. Analysis of the Results

4.1. Spatial structure evolution characteristics of aviation network

4.1.1. Topology evolution of aviation network

Between 2010 and 2019, China's transportation network system saw significant improvements. The number of major air routes and city points increased, expanding the overall scale range of the aviation network and leading to more frequent air passenger connections between cities (Table 2.). In 2010, the aviation network encompassed 60 city points and 239 routes. By 2015, this had grown to 65 city points and 299 routes, representing a year-on-year increase of 25.10% in the number of routes. By 2019, the aviation network covered 70 city points and 430 routes, with the number of routes increasing by 43.81% year-on-year. Moreover, the overall scale quality of the aviation network steadily improved, with the average degree value increasing from 1.453 in 2010 to 1.866 in 2019 – a 1.28-fold increase. This indicates that the total number of air passenger traffic connected to the outside of a single city point continued to grow, with the strength of the city point's external air passenger connections becoming greater.

The clustering coefficient of the "small world" feature network is larger, and the average path length value is smaller when compared to the theoretical value of the randomized network of equal size [49]. The clustering coefficient decreased to 0.639, representing a decrease of up to 9.62%, and the total number of airline network routes to city points increased, thereby optimizing the entire aviation network structure. It is noteworthy that the average path length showed a trend of first decreasing and then increasing, indicating a substantial increase in aviation network connectivity efficiency in 2015. However, the significant increase in the total number of routes in 2019 led to a small decrease in the aviation network connectivity efficiency, as the total amount of passenger traffic that needed to be diverted from different city points significantly increased. Compared with the theoretical value of the ER random equivalent size network, the difference between the two clustering coefficients kept decreasing, and the gap between the average path lengths kept expanding. This suggests that the density between city points of the real aviation network decreased, while the degree of external dependency and aviation network connectivity efficiency significantly increased. Overall, the organization efficiency of the aviation network has been improving, while the "small world" effect has weakened. There is still room for improvement of the aviation network connectivity.

Table 2. The topological characteristics of overall aviation network in China

Year	Number of cities	Number of routes	Average degree values	Clustering coefficients	Average path length	ER random scale network values	
						Clustering coefficients	Average path length
2010	60	239	1.453	0.707	2.150	0.116	2.171
2015	65	299	1.686	0.688	2.124	0.160	2.083
2019	70	430	1.866	0.639	2.143	0.177	1.916

Utilizing the spatial structure analysis of the "axis-spoke" aviation network by Jin et al. (2005) [50], China's aviation network during 2010-2019 displays three distinct spatial characteristics (Figure 1.). Firstly, the aviation network underwent a gradual transformation into a "double rhombus-single axis" spatial pattern of the axis-spoke network, with an increased number of axis cities. The fundamental "double rhombus - single axis" structure emerged in 2015 with the addition of Shenzhen, Chongqing, and Xi'an. Further, in 2019, Hohhot joined the "single axis" and bolstered the passenger transport links between each axis city, thus strengthening and stabilizing the "double rhombus - single axis" structure. Secondly, the aviation networks at level 2 and level 3 transitioned into intermediary networks to establish a more robust connection between the "double rhombus" and "single axis" regions, utilizing Xi'an-Chongqing-Kunming as the intermediary axis. This network type is primarily distributed among axial cities in the double rhombus region, with the network complexity increasing due to the growth of passenger traffic diversion in the axial cities, which gradually established numerous closely connected corridors. Lastly, the aviation networks at level 4 and level 5 were distributed in the form of "point-to-point" networks, serving a critical role in improving regional aviation accessibility as the underlying network during 2010-2019. These networks have continuously reduced reliance on the "double rhombus -

single axis" network and improved network complexity. By doing so, they have diminished dependence on the "double rhombus-uniaxial" network, ultimately attaining a balance of network sharing and a more uniform distribution of air traffic.

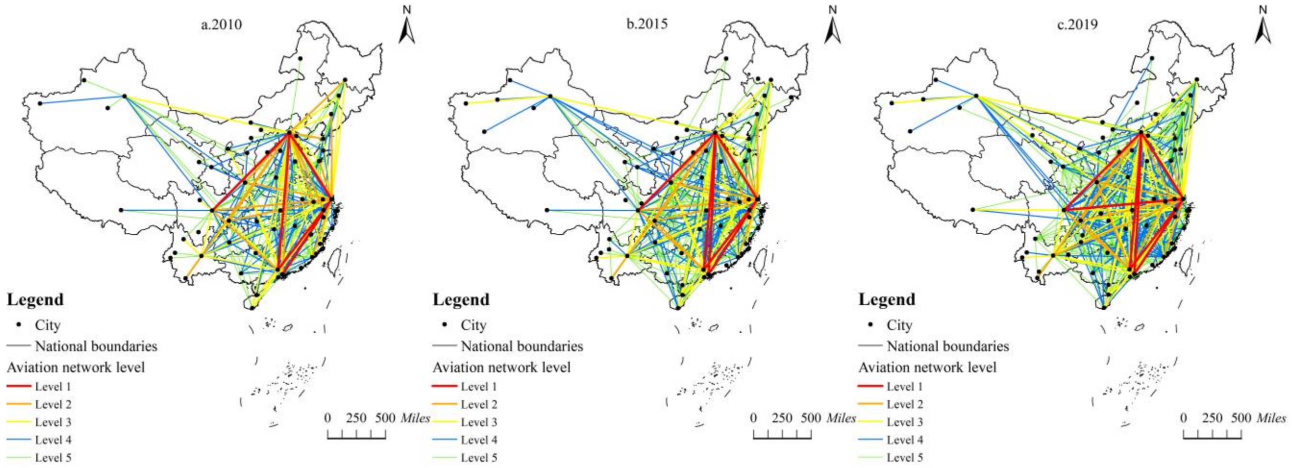

Figure 1. The evolution of spatial structure in China's aviation network

4.1.2. Spatial structure evolution of the dominance degree of aviation network

To comprehensively assess the aviation dominance of major cities in China, this study measured and visualized the aviation network dominance in 2010, 2015, and 2019 using the ArcGIS natural fracture method (Figure 2.). There are three main characteristics of the spatial structure of the aviation network dominance of Chinese cities between 2010 and 2019. Firstly, the number of cities at level 1 and level 2 has remained relatively stable, and their spatial distribution is in line with the "double rhombus-single axis" structure of the axis cities. Secondly, the number of cities at level 3 has seen the most change, increasing by 57.14% compared to 2010, and exhibiting remarkable spatial spread, with clustering and distribution characteristics in the "double rhombus" network. These new cities are primarily located in the central and western regions, including Wuhan and Changsha, which have enhanced their aviation scale advantages due to faster economic development, and Lanzhou and Guiyang, which have improved their ranking due to their attributes as intermediary "hubs" connecting the western and northwestern regions, increasing their aviation openness. Guiyang's attributes as a tourist city have also brought in significant tourism air traffic, contributing to its expanding aviation influence. Finally, the cities at level 4 and level 5 are mainly the capital cities of central and eastern provinces and western tourist cities, which are spatially scattered in the peripheral or outer areas of the "double rhombus" network, and their number is generally decreasing. This decline can be attributed to their limited aviation openness, which constrains the total scale of passenger traffic in their own route networks, leading to weaker aviation advantages.

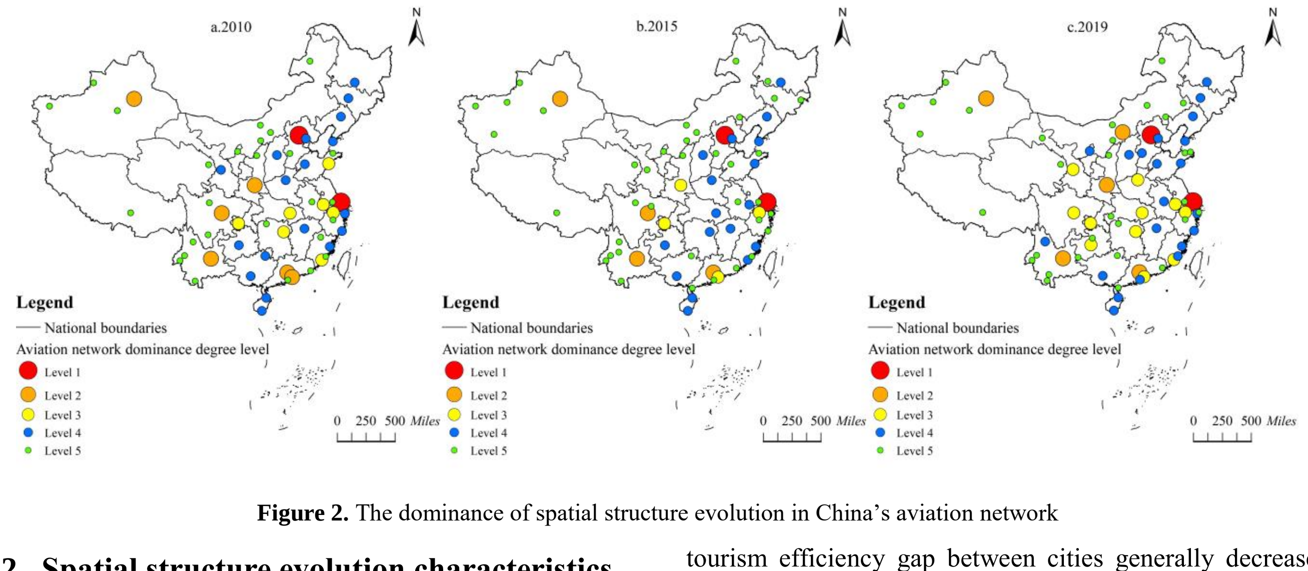

Figure 2. The dominance of spatial structure evolution in China's aviation network

4.2. Spatial structure evolution characteristics of tourism efficiency network

4.2.1. Spatial structure evolution of tourism efficiency

In this study, we utilized the input-output data presented in the previous section to assess tourism efficiency in various Chinese cities between 2010 and 2019 (Figure 3.). Our analysis revealed two main characteristics of the spatial structure of tourism efficiency during this period. Firstly, the tourism efficiency gap between cities generally decreased, while the trend of cities at level 2 and above forming clubs became more apparent, especially in the southwest region where the development potential shifted towards the west. In 2010, three club groups had formed, including Guangzhou-Shenzhen, Wuxi-Shanghai, and Dehong-Xishuangbanna. However, in 2019, the number of cluster clubs had increased to three, including Southwest, Guangzhou-Shenzhen-Zhuhai, and Beijing-Tianjin, with a significant expansion in the scale and spatial distribution of these clusters. Moreover, the number of cities at level 3 and above remained relatively constant, accounting for 20-25% of the total, primarily composed of cities with a strong economy and rich tourism resources. These cities were mostly concentrated on the east side of the "Hu Huanyong" line, indicating the spillover effect of a vast market demand on tourism efficiency due to population scale. Secondly, the cities at level 4 and level 5 were dispersed across the country with little spatial order, suggesting a "spatial and temporal convergence" effect in the development of tourism efficiency. In particular, the 5th rank cities formed a "collapse zone" for tourism efficiency development. The emergence of cities at level 4 and level 5 in the central and eastern regions could be attributed to the expansion of the accommodation and catering industry and an exponential increase in the number of employees compared to 2010 and 2015. Such input factors, to some extent, reduced the efficiency of tourism scale economies. Conversely, in the western regions, tourism efficiency development was impeded by a scarcity of input factors such as resources, human and capital. Additionally, despite the abundance of tourism resources in the Inner Mongolia-Gansu-Ningxia plate, the "collapse" of its economy limited tourism efficiency due to inadequate economic support facilities.

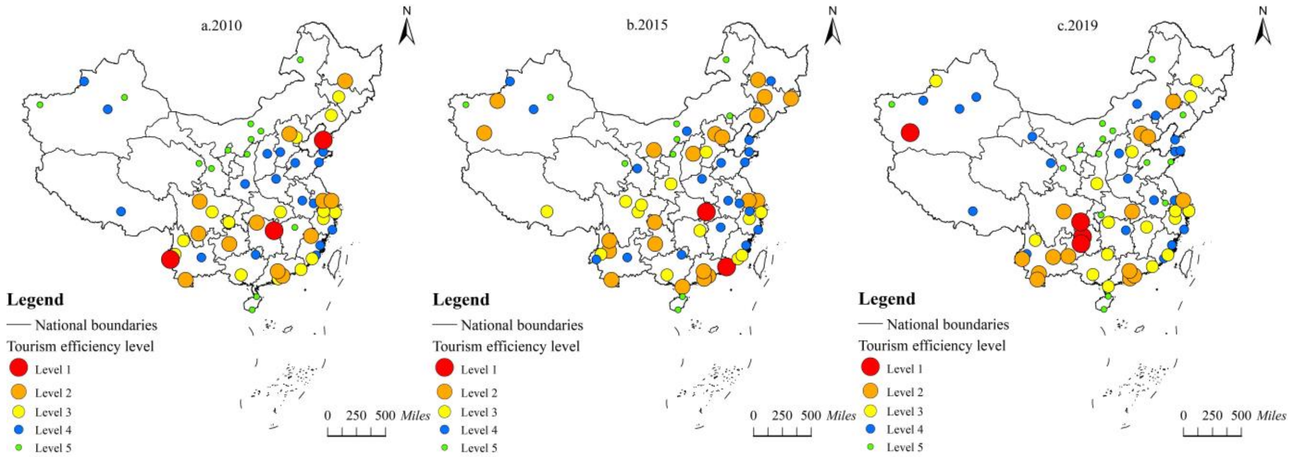

Figure 3. The spatial structure evolution of China's tourism economic efficiency

4.2.2. Topology evolution of tourism efficiency network

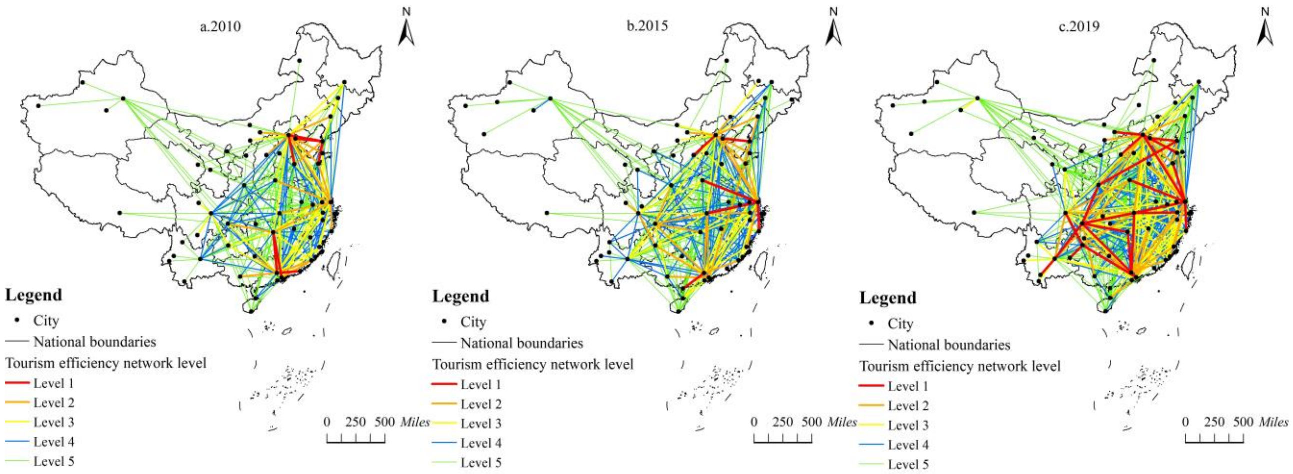

Figure 4. The spatial structure evolution of China's tourism efficiency network

Utilizing the tourism efficiency data of each city to measure inter-city tourism efficiency links, an OD matrix network was generated and visualized as illustrated in Figure 4. Based on traditional topological network type classification criteria, China's tourism efficiency network exhibits two primary characteristics during 2010-2019. Firstly, the tourism efficiency network is gradually adopting a "honeycomb" structural form consisting of a topological network comprising "point-to-point" and "star-shaped" (i.e., a network around the core city points to form a network of outward diffusion, with no connection between the outward diffusion city points) layouts connected to the tourism efficiency of inter-city links. The number of "star" networks increased from 7 in 2010 to 10 in 2019, and the tourism efficiency network is now dominated by "star" networks at level 1 and level 2. In the overall network, the intensity of external tourism efficiency linkages is increasing, and the spatial distribution of the network is concentrated in the eastern region, with the number of regional "star" networks increasing, significantly influencing the overall network density. Secondly, the total number of tourism efficiency links in the overall network follows "Pareto's law," with "star" networks occupying the majority of the total number of links. The "tree" and "mesh" networks at level 4 and level 5 have a significant impact on the overall network density and compete with each other in terms of tourism efficiency. The "star" networks of each level increased their total number of links from 63% in 2010 to 85% in 2019. The "tree" network of level 4 is highly dependent on high-ranking cities and has fewer tourism efficiency links between network nodes of the same level. On the other hand, the "mesh" network of level 5 has fewer tourism efficiency links but more external tourism efficiency linkage paths. The strength of tourism efficiency network linkage is poor, and the scale and complexity of both network systems are high, indicating that tourism efficiency linkage between cities is in a state of scale diseconomies.

5. Double Network Interaction Impact Analysis

5.1. Overall network interaction impact test

To further investigate the mechanisms of interaction between multi-level difference networks, we analyzed the influence of tourism efficiency element difference networks on the relationship strength of aviation networks, as well as the impact of aviation dominance element difference networks on the relationship strength of tourism efficiency networks. This led to the evolution of the spatial multi-level structure of aviation networks and tourism efficiency networks as the underlying logic. To achieve this, we conducted multi-level network correlation and QAP regression analysis using 10,000 random permutations selected by Ucinet 6.0. The results of our analysis are presented in Tables 3, 4, and 5.

Table 3. The interaction test of aviation network and tourism efficiency network

Year	Correlation coefficient	QAP regression coefficient	R2
2010	0.501***	0.356***	0.251***
2015	0.512***	0.387**	0.262***
2019	0.523***	0.431***	0.273***

Note: ***, **, * in the table represent 1%, 5%, 10% significant level respectively

We presented the results of the QAP correlation and regression analysis between the aviation network and tourism efficiency network (Table 3.). The correlation coefficients are 0.501, 0.512, and 0.523, respectively, while the QAP regression coefficients are 0.356, 0.387, and 0.431, with corresponding R-squared values of 0.251, 0.262, and 0.273. The significance level tests confirm that these results are statistically significant at P<0.01. The positive correlation between the aviation network and tourism efficiency network is increasing, as indicated by the QAP correlation coefficients, indicating a trend of synergistic evolution between the two networks. More than half of the variances of each other are correlated, and this correlation is reflected in the "double rhombus - single axis" spatial structure core of the aviation network. Specifically, the "honeycomb" network of tourism efficiency is the primary way to evolve the "cellular" network of tourism efficiency, while the "star" network of the western region of the tourism efficiency network in 2019 is the "multi-axis" network of the aviation network's main component of network evolution.

The QAP regression and R-squared results indicate that the explanatory power of the aviation network on the tourism efficiency network is continuously improving. The cumulative explanation of tourism efficiency network variation reached 27.3% in 2019, demonstrating the importance of the aviation network's role in the evolution of the tourism efficiency network. The consolidation and optimization of the "double rhombus-single axis" spatial structure of the aviation network have resulted in the improvement of the number of hubs in the network, which has a "long tail" effect on the formation and evolution of the tourism efficiency "star-shaped" network. This "effect" means that the economic non-developed areas can leverage their unique air corridors and tourism resources to enhance their tourism economic attractiveness.

5.2. Factor difference network interaction effects test

5.2.1. Test of interaction between aviation factors' difference network and tourism efficiency network

Based on the QAP correlation and regression analysis of the aviation factor difference network with the tourism efficiency network for 2010-2019 (Table 4.), the positive correlation coefficients of the difference matrices of the four independent variables with the tourism efficiency network all pass the significance test. However, their correlation levels are decreasing, indicating that the differences between the aviation factor indicators of each city are decreasing and their correlation with the structure of the tourism efficiency network is decreasing as well.

Table 4. The interaction test of aviation factors' difference networks and tourism efficiency network

	ASA		*AOP*	
Year	Correlation coefficient	QAP regression coefficient	Correlation coefficient	QAP regression coefficient
2010	0.529***	0.254***	0.476***	0.192***
2015	0.513**	0.247***	0.457**	0.176***
2019	0.487**	0.225***	0.411**	0.163***
	AIP		*AI*	
Year	Correlation coefficient	QAP regression coefficient	Correlation coefficient	QAP regression coefficient
2010	0.455***	0.188***	0.518***	0.246***
2015	0.438**	0.169***	0.509**	0.228***
2019	0.383**	0.144***	0.484***	0.212***

Note: ***, **, * in the table represent 1%, 5%, 10% significant level respectively

The regression coefficients of all dependent variables pass the significance test and the R2 is in the range of 0.214-0.353 (with all significance below 1%), indicating that the differential network of aviation factors has good explanatory power on the relationship of tourism efficiency network. The difference matrices of aviation scale advantage and aviation influence have the most prominent positive influence on the tourism efficiency network, indicating their important role in improving the scale and structure of tourism passenger flow, and strengthening the inter-city tourism efficiency network relationship. Conversely, the difference matrices of aviation openness power and aviation intimacy power have relatively low positive influence on the tourism efficiency network, indicating that the influence of long-distance multi-source passenger flow on inter-city synergistic development of inter-city tourism efficiency relationship is decreasing with the development of peripheral and intra-provincial tourism. According to the law of tourism distance decay, most of the city tourism income comes from the surrounding areas with close tourism relations, and the tourist sources of each city tourism market exist in the way of high-speed rail, highway, and other alternative competition. The scale of passenger traffic in the air channel of cities with high tourism efficiency gravity level is more stable, making the optimized tourism efficiency network structure have an obvious "path locking" effect. Thus, the role of improving the level of accessibility to tourism traffic in the central and western part of the country is not significant, leading to a decline in the level of aviation development on the city tourism efficiency network relationship.

5.2.2. Test of interaction between tourism economic factors' difference network and aviation network

In the QAP correlation and regression analysis of the difference network of tourism efficiency elements and the aviation network, the results for the period of 2010-2019 indicate that the correlation coefficients of the difference matrix of the five independent variables with the aviation network relationship matrix all passed the significance level test. As this econometric model solely focuses on a difference matrix, the correlation coefficient in Table 5. is positive, indicating that the greater the difference of tourism efficiency elements among cities, the greater the air passenger flow, and the more rapidly the direction of flow changes, resulting in a higher correlation with the formation and evolution of aviation network relationships. A negative correlation coefficient indicates that the smaller the difference of tourism efficiency elements, the greater the similarity between cities, leading to a stronger balance of air passenger flow, and a higher correlation with inter-city aviation networks.

Table 5. The interaction test of tourism efficiency factors' difference networks and aviation network

	TRE		*TLA*		*TCA*	
Year	Correlation coefficient	QAP regression coefficient	Correlation coefficient	QAP regression coefficient	Correlation coefficient	QAP regression coefficient
2010	0.477***	0.281***	0.488**	0.276***	0.495**	0.229***
2015	0.504***	0.358***	0.539**	0.301***	0.513**	0.235***
2019	0.529***	0.464***	0.555***	0.368***	0.534***	0.323***
	TRC		*TMS*			
Year	Correlation coefficient	QAP regression coefficient	Correlation coefficient	QAP regression coefficient		
2010	-0.431**	-0.345***	-0.385**	-0.254***		
2015	-0.511***	-0.410***	-0.416**	-0.351***		
2019	-0.545***	-0.431***	-0.508***	-0.422***		

Note: ***, **, * in the table represent 1%, 5%, 10% significant level respectively

From the regression results, all dependent variables' R2 values range from 0.271 to 0.426, passing the 1% significance test, and the regression coefficients also pass the significance test. These results suggest that the independent variables of tourism efficiency index can better explain the changes of the spatial structure of the aviation network. Among the independent variables, the regression coefficients of the difference matrices of the three independent variables of tourism resource endowment, tourism labor advantage, and tourism capital advantage keep increasing. They have a positive driving effect on the formation of aviation network relationships and their positive effect strengthens over time. The positive effect of tourism resource endowment is reflected in the fact that the greater its difference, the more cities with better resources can attract a large amount of air passenger flow, thus improving the aviation network structure. The difference of tourism labor advantage and tourism capital advantage essentially reflects the difference in tourism core industry development scale between cities. The positive effect of tourism core industry development scale is reflected in the fact that the larger the difference, the larger the scale of the city's ability to connect with external air passenger flow. The "Star" topology channel to the surrounding air traffic "siphon effect" makes the passenger flow concentrated in the air traffic "double rhombus" channel, further consolidating the original structure of the aviation network and generating new hubs.

However, the regression coefficients of tourism revenue capacity and tourism market size are negative, both of which are tourism output indicators and have a negative effect on the structural optimization of the aviation network. This indicates that the differences in tourism output are narrowing, which is more conducive to the establishment of strong aviation network relations. As urban tourism efficiency in China has grown, a trend towards self-organization of aviation network passenger flows influenced by market demand has emerged. This trend is due to the narrowing of differences in urban tourism output, and has resulted in the creation of numerous low-grade routes. Unfortunately, this trend has had a negative impact on the overall efficiency of the aviation network by suppressing its circulation.

6. Conclusions and Policy Implications

6.1. Conclusions

This study applies a range of analytical methods, including complex network analysis method, the entropy-weighted TOPSIS method, the Super-SBM model, tourism efficiency gravity model, and the quadratic assignment procedure, to examine the evolution of the spatial structure and interaction mechanisms between the aviation network and tourism efficiency network of major Chinese cities at three points in time: 2010, 2015, and 2019. The principal outcomes of the analysis are presented below.

Firstly, the efficiency of aviation network organization has been gradually improving in China, however, the "small world" effect has weakened and there is still room for improving the connectivity of the aviation network. The spatial evolution of China's aviation network has resulted in a "double rhombus-single axis" axis-spoke network pattern, where the number of axis cities has increased and the balance of the network has greatly improved. The cities at level 2 and level 3 have become part of the intermediary axis-spoke network with Xi'an-Chongqing-Kunming as the intermediary axis, strengthening the central and western regions. The aviation networks at level 4 and level 5 remains distributed in a "point-to-point" spatial structure. The spatial distribution of the cities at level 1 and level 2 aligns with the axis cities of the "double rhombus-single axis" network, and the dominance of the aviation network has significantly increased. Moreover, the number of "intermediary" hub cities in the western region has been on the rise.

Secondly, the tourism efficiency network has adopted a "honeycomb" structural pattern in China, which includes both "point-to-point" and "star" topological networks. This structure facilitates tourism efficiency linkages among urban points. The total tourism efficiency linkage of the network follows Pareto's Law, with significant competition among the cities at level 4 and level 5 in "tree" and "mesh" networks. The tourism efficiency among cities is decreasing, with a clear trend toward the formation of clubs in the group of cities above the cities at level 2 . The potential area of tourism efficiency development is shifting to the southwest, while the cities at level 4 and level 5 are dispersed across the country, exhibiting a high degree of disorder. These trends illustrate the "spatial and temporal convergence" effect of the convergence of tourism efficiency development.

Thirdly, the co-evolution of China's aviation network and tourism efficiency network is becoming increasingly apparent, with more than half of their variances showing a correlation. The aviation network's explanatory power on the tourism efficiency network is on the rise, with its cumulative degree of variance explanation reaching 27.3% in 2019. The differential networks of tourism efficiency factors and aviation network are mutually interactive, with differences in tourism resource endowment, labor advantage, and capital advantage having positive effects on aviation network structure changes. Conversely, differences in tourism revenue capacity and market scale have negative effects. The aviation factor difference network and tourism efficiency network formation have interactive effects, where the positive influence of aviation scale advantage, openness, intimacy, and influence on the tourism efficiency network structure is decreasing. Moreover, there is an apparent "path dependence" effect in optimizing the tourism efficiency network structure.

6.2. Policy implications

Given the aforementioned findings, the following recommendations are suggested for the advancement of air traffic planning and tourism efficiency in China.

Firstly, to enhance the development of air traffic planning in China, we recommend accelerating the construction and development of the four regional "single-axis" aviation networks, prioritizing route planning to regional non-axis and "single-axis" cities, and establishing more multi-level aviation connections to cities in the western region. Additionally, efforts should be made to improve the aviation infrastructure of "intermediary" hub cities in the western region to promote their growth and consolidation as a prominent force in the "double rhombus" network structure. Lastly, we suggest accelerating the layout of routes to cities in both the east and west to enhance regional links.

Secondly, the southwest and Xinjiang regions have emerged as the central zones for sustainable development of tourism efficiency in China, thanks to their abundant and distinctive tourism resources and relatively comprehensive tourism infrastructure. It is recommended that the southwest and Xinjiang regions should be prioritized as key investment and construction areas for tourism efficiency development in China. Furthermore, the acceleration of tourism infrastructure facility construction in Inner Mongolia is imperative to create the necessary foundations for tourism development, including high-quality tourist attractions, accommodation hotels, catering centers, travel agencies, and more, to form the basis of tourism development in the less developed areas.

Thirdly, to enhance tourism development in cities with a high aviation network advantage but low tourism efficiency, such as Urumqi and Hohhot, it is crucial to fully exploit their potential tourism resources. Achieving regional linkage development can be realized by strengthening connections with high-grade tourism cities. Focusing on improving development efficiency, employing experts and scholars to formulate tourism special planning, innovating tourism product business modes, and digitalizing tourism AI can also help. For cities with high tourism efficiency but low aviation network advantage, such as Hotan and Xishuangbanna, increasing air traffic construction and enhancing external connectivity through improved accessibility levels are necessary.

Author Contributions

Conceptualization, X.G.; J.H.; methodology, H.C.; software, H.C.; validation, X.G., H.C. and J.H.; formal analysis, X.G.; data curation, H.C.; writing—original draft preparation, H.C.; writing—review and editing, X.G., J.H.; visualization, X.G.; supervision, J.H.; funding acquisition, X.G., J.H.; All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest

The authors declare no conflict of interest.

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