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Study on the Correlation Characteristics between Scenic Byway Network Accessibility and Self-Driving Tourism Spatial Behavior in Western Sichuan

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Abstract: The scenic byways in Western Sichuan are some of the most popular self-driving tourism destinations in China. However, the current network of scenic byways in the region is not well-coordinated with the level of regional tourism development. This paper, based on travel digital footprints, uses methods such as spatial design network analysis, GIS spatial analysis, social network analysis models, and spatial econometric models to analyze the accessibility and self-driving tourism spatial behavior characteristics in Western Sichuan. The main research results are as follows: (1) the accessibility level of scenic byways in Western Sichuan exhibits significant spatial variation, with the majority of areas demonstrating moderate to poor accessibility; (2) the network structure of self-driving tourism spatial behavior displays characteristics of low overall network density, but with a high clustering coefficient and relatively short average path length, indicating a significant small-world phenomenon. All network node indicators exhibit significant heterogeneity, with the core nodes displaying clear clustering characteristics; (3) the accessibility of scenic byways and self-driving tourism spatial behavior exhibit significant spatial spillover effects. This study analyzes the relationship between the accessibility of scenic byways and self-driving tourism spatial behavior in Western Sichuan, providing valuable insights for the planning and construction of scenic byways and the development of self-driving tour routes.

Keywords: accessibility; self-driving tourism spatial behavior; spatial analysis; scenic byway; Western Sichuan

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1. Introduction

Transportation plays a crucial role in supporting the tourism industry, serving as a fundamental factor for its success [1]. The integrated development of transportation and tourism is based on the accessibility provided by transportation infrastructure. A well-designed transportation network enhances the convenience of tourist travel and promotes the comprehensive and harmonious development of transportation, tourism, culture, and economy in a region [2,3]. Research has shown that systematic transportation planning and policies contribute to improving the overall travel experience and satisfaction of tourists [4,5].

In recent years, scenic byways have garnered increased attention as significant infrastructural elements that integrate transportation and tourism, particularly due to the rapid development of China's economy and society [6]. In 2016, the Chinese government introduced the "National Ecotourism Development Plan", which outlined the construction of 25 national scenic byways. Subsequently, in 2017, "Opinions on Promoting the Integrated Development of Transportation and Tourism" was published, with the objective of establishing a comprehensive system of tourism scenic byways and actively promoting their construction [7].

Among the Chinese provinces, Sichuan stands out for its abundant tourism resources and well-developed tourism industry. In July 2023, Sichuan Provincial Government unveiled the "Plan for Building World-renowned Tourist Destinations in Sichuan (2023–2035)", which aims to establish a world-class scenic byway network. The western region of Sichuan Province is characterized by its high-altitude mountainous terrain and abundant tourism resources, making it one of the most popular destinations for self-driving tourism in China. Related studies indicate that Western Sichuan is rich in natural and historical cultural resources. In order to effectively utilize these resources, the establishment of an ecological and cultural heritage tourism corridor spatial system is recommended. This system should revolve around the main axes of National Highway 317 and National Highway 318, with core nodes centered around cities such as Chengdu, Kangding, Litang, and Garze [8,9].

The natural geographical environment is a major determinant of transportation infrastructure, and, compared to plain areas, mountainous regions face challenges in establishing robust transportation networks. Due to the extremely complex natural environment and harsh geological conditions, the density of scenic byways, road capacity, and overall service quality in Western Sichuan are relatively low, and their support for the development of tourism resources along these routes is limited [10,11]. Essentially, these problems stem from the unbalanced and uncoordinated development between the transportation infrastructure of scenic byways and regional tourism. Analyzing the accessibility and self-driving tourism spatial behavior in Western Sichuan's scenic byways is of great significance for further expanding the tourism market, improving the level of integration between transportation and tourism, and promoting regional economic and social sustainability. This study can also provide valuable insights for government agencies, tourism destination planners, and tourism service providers in areas such as transportation network and tourism infrastructure development.

Previous research has mainly focused on aspects such as the planning and construction of scenic byways [12], landscape assessment and design [13], and tourism development [14], with relatively limited studies on the impact of scenic byways on tourism spatial behavior. To address the challenges posed by the imbalance between tourism transportation supply and demand, improve the accessibility of scenic byways, and improve the coordination between the development of self-driving tourism and regional transportation networks in Western Sichuan, this paper investigates the relationship between the accessibility of scenic byways and self-driving tourism.

This study uses methods such as GIS spatial analysis and social network analysis models to construct models for measuring the accessibility of scenic byways and the network structure of self-driving tourism in the Western Sichuan. It examines the accessibility of scenic byways and the level of self-driving tourism development in different regions of Western Sichuan and analyzes the characteristics of self-driving tourism spatial behavior. This research contributes to the understanding of the current layout of the scenic byway network (route system and node system) and the development level of self-driving tourism in Western Sichuan. It also provides insights for the scientific and rational layout of the scenic byway network in this region.

2. Literature Review

2.1. Scenic Byway

Researchers generally agree that the definition of scenic byways can be broadly categorized into two types: a broad definition refers to roads with dual functions of transportation and scenic appreciation, while a narrow definition refers to high-quality roads that possess scenic, natural, cultural, historical, recreational, and archaeological values within or visible from their surroundings [15,16]. The United States is the birthplace and practical ground for scenic byways. In 1991, the United States introduced The National Scenic Byways Program (NSBP). As of 2021, there were more than 180 nationally designated byways in the United States, including 150 National Scenic Byways and 37 All-American Roads, covering 48 states [17].

Scenic byways in different countries have different names, including Scenic Road, Scenic Route, Tourist Road, Tourist Route, etc. Norway has 18 National Tourist Routes, mainly featuring natural landscapes. The "Scenic Routes project" in Norway has achieved significant success in attracting tourists and promoting Norwegian architecture [18]. Germany has introduced various theme routes such as the Romantic Road, the Wine Road, and Castle Road, which have been well-received by tourists [19,20]. Japan's "Historical Routes Policy" emphasizes the protection of the routes themselves and the related heritage along the routes. Scenic byways were introduced to China around 2000. Since 2016, the Chinese government has issued several policies encouraging the integration of transportation and tourism, which has accelerated the planning and construction of scenic byways in China [21].

Compared to conventional tourist roads that primarily facilitate transportation between tourist destinations, scenic byways represent a distinct type of tourism road that integrates multiple values, including scenic, transportation, recreational, ecological, and cultural, all within a visible range. In essence, scenic byways function as self-contained tourist destinations. By adopting a collaborative development model for tourist attractions, scenic byways undergo a transition from isolated "nodes" to interconnected "routes", effectively encompassing a broader "area" and breaking away from the isolation typically associated with traditional destination-centric tourism nodes. This approach holds significant potential in fostering comprehensive tourism experiences [22].

2.2. Accessibility

Transportation, as an important carrier of spatial flows such as passenger flows, logistics, information flows, and capital flows, is an integral part of the tourism system. Due to the immobility of tourism resources, the spatial displacement of tourism flows relies heavily on the regional transportation system, which provides essential support for the development of the tourism industry [23]. Scholars have studied the impact of transportation on the tourism industry from the perspective of transportation accessibility [24]. They believe that transportation is crucial to the development of tourism because it directly links supply and demand, providing accessibility to tourist destinations.

In 1959, Hansen [25] first introduced the concept of accessibility, defining it as the degree of mutual influence between different transportation nodes. Since then, many scholars have expanded the concept of accessibility. Lenntorp [26] views accessibility as the physical spatial environment that can be reached under temporal and spatial constraints, emphasizing the constraints in both time and space dimensions. Maćkiewicz [27] and Shen [28] have pointed out that accessibility is a crucial factor contributing to regional spatial development disparities and serves as an indicator of the depth and breadth of geographic relationships between regions. Transportation accessibility refers to the ease of overcoming obstacles and establishing connections between different locations by different modes of transport. It is a critical reference indicator for measuring the level of smoothness of transportation between different regions [29].

As scholars continue to expand the application areas of accessibility, the methods and models for accessibility evaluation have also been continuously enriched. Luo et al. [30] used the weighted average travel time method and gravity model to calculate and analyze the accessibility of railway transportation in the Greater Bay Area of Guangdong, Hong Kong, and Macau. Based on spatial syntax and network analysis theory, Yang et al. [31] considered various aspects of public transportation network configuration, such as service frequency, topological structure, and geographical layout, as well as potential travel demand and attractiveness. The study comprehensively used centrality and gravity models to evaluate the accessibility of public transportation. Gu et al. [32] conducted a comprehensive evaluation of the layout and accessibility of green spaces in Nanjing using spatial syntax models, considering global integration, local integration, and intelligibility. From the perspective of spatial design network analysis, Zhou et al. [33] calculated the accessibility and centrality of the road network in the Chengdu-Chongqing Economic Circle based on four indicators: closeness, traversability, detour rate, and efficiency.

Many scholars have studied the impact of accessibility on spatial patterns and their evolution. The evolution of regions and the development of transportation networks are spatially interactive processes, with the transportation system determining the spatial accessibility of regions. Cao et al. [34] pointed out that regions with higher transportation accessibility exhibit stronger spatial agglomeration effects. Zhou et al. [35] indicated that expanding the construction of internal road networks in transportation-disadvantaged counties is beneficial for promoting spatial equity in the distribution of transportation resources. Through empirical research in Indian villages, Sarkar et al. [36] found that road networks located at the center of blocks or neighboring urban villages had higher centrality and efficiency, and there was a significant positive correlation between road network connectivity and accessibility. Wu et al. [37] used data from high-grade scenic spots in Inner Mongolia and the nearest neighbor index, kernel density, and spatial autocorrelation to systematically analyze the spatial distribution patterns, accessibility. Their research indicated that the spatial distribution of tourist attractions in this region shows a pattern of "small agglomeration and large dispersion".

2.3. Self-Driving Spatial Behavior

Research on self-driving spatial behavior mainly focuses on tourists' consumption behavior, spatial differentiation characteristics, and travel chains. Gronau et al. [38] analyzed questionnaire-based statistical data and found a strong positive correlation between the layout of tourism transportation networks and travel behavior choices. Gardner [39] and Vance [40] conducted a questionnaire survey of self-driving tourists, considering factors such as road travel costs, travel time, and destination choices. They found that travel costs play a critical role in self-driving travel decisions. Eby et al. [41], through a questionnaire survey of American self-driving tourists, identified accessibility and distance as the main influencing factors. Can et al. [42] analyzed the consumption and decision-making characteristics of self-driving tourists and found that the ratio of travel cost per kilometer to income is a key factor in their travel route decisions.

With the development of Internet technology, researchers have shifted from traditional survey methods such as questionnaires and travel diaries to using big data approaches such as online travel journals, photographs, and other "tourism digital footprints" to study the spatial structure of self-driving travel, spatial patterns of self-driving tourism, and macro-level behavioral characteristics such as tourist flows.

Zhao et al. [43] conducted research on the self-driving tourism market and network structure characteristics in Fujian Province, based on data mining from online travelogues. They used a combination of social network analysis methods, GIS, and mathematical statistics techniques. The study indicated that, within the research area, there was a strong imbalance in network node statuses, with significant polarization. The interaction frequency among core nodes was much higher than that among peripheral nodes. The spatial distribution showed a pattern of "overall dispersion with local concentration".

Luo et al. [44] examined the spatiotemporal characteristics of self-driving tourist passenger flows in Yunnan Province using two types of "digital footprints", namely online travelogues and photos. The research showed that self-driving passenger flows exhibited a high degree of concentration in terms of travel times, with peak flows occurring during winter and summer vacations, as well as during the National Day holiday. The source of tourists was mainly distributed around Yunnan and eastern China. The self-driving space exhibited an overall distribution pattern characterized by multiple cores, multiple linear shapes, and multiple regions. The network had a relatively low density, and its structure showed clear stratification, with core tourist areas not exerting strong driving forces on peripheral tourist areas.

Zheng et al. [45] collected digital footprints of self-driving tourists in western Hunan and, in conjunction with OSM road network data and tourist attraction POI data, used grid calculators, standard deviation ellipse analysis, and buffer analysis methods. This research investigated the layout of the regional scenic byways. It was found out that tourist points of interest were prominently distributed along the roads, forming a scenic byway layout characterized as "one main route with one subsidiary and multiple branches".

Liu et al. [46] conducted a study on the self-driving tourism hotspots in Tibet using GPS trajectory mining, OSM road network data, and tourist attraction POI data. The study found that the natural scenery around national highways had a strong attraction for self-driving tourists. Self-driving tourists tended to cluster around tourist attractions, with visitors stopping and resting at parking lots, service stations, scenic road sections with beautiful views, and tourist spots. The overall rhythm of tourist activities combined both mobility and rest, with most of the time spent in a mobile state.

2.4. Transportation and Tourism

Regarding the impact of transportation on the spatial structure of tourist destinations, Smallwood et al. [47] analyzed the relationship between tourism spatial patterns and regional transportation networks, and their study showed that improving the layout of the tourism transportation network significantly increases the efficiency of road travel. Pellegrini et al. [48] considered that land transportation is an important factor influencing tourism demand and tourists' length of stay. Huang et al. [49] pointed out that the development of high-speed railway has a greater impact on the tourism system of urban agglomerations, strengthening the core–periphery structure of the urban agglomeration tourism system, with the peripheral cities being more affected. Li et al. [50] indicated that transportation development has significantly compressed time and space within the region, resulting in the evolution of the spatial structure of the regional tourism system from a "strip" pattern to a combined "spot-axis-surface" form known as "blocks".

In terms of the coupling and coordination mechanism between transportation and tourism, Wang et al. [51] pointed out that optimizing transportation networks and promoting coordinated development of tourist destinations can lead to synchronized optimization of the coupling degree of both, facilitating a positive interactive relationship between tourist destinations and transportation networks. Wang et al. [52] emphasized the dynamic and mutually reinforcing coupling relationship between transportation networks and the development of tourism spatial structures. Mao et al. [53] found that the spatial coupling relationship between tourism formats and transportation networks is the result of element aggregation and functional spillover effects in the tourism process.

In terms of the coordinated relationship between tourism development and transportation level, Zou et al. [54] pointed out that transportation accessibility and the length of highways are important factors influencing tourism development. Xu et al. [55] emphasized that regions with relatively developed tourism industries should maintain the development of transportation, while regions with a well-established foundation in tourism development will experience a significant increase in transportation flow, thus promoting the development of transportation level.

The theories of new economic geography indicate that the heterogeneity and proximity of geographical space influence and determine the industrial collaboration and development spillovers between different regions, and the existence of spillover effects will promote regional coordinated growth [56,57]. Given the inherent spatial coupling between transportation and tourism development, scholars have conducted research on the spatial spillover effects arising from transportation on regional tourism development and the spatial structure of tourist flows.

Guo's et al. [58,59] research on the Yangtze River Economic Belt and Yunnan shows that high-value tourism economic zones are highly dependent on regions with highly developed road transportation. The level of self-driving tourism development shows remarkable spatial heterogeneity, and its spillover and diffusion simultaneously promote the development of transportation levels. Wang et al. [60] pointed out that the uneven regional tourism development and infrastructure construction not only have a negative direct impact but also show significant negative spatial spillover effects.

In summary, researchers have conducted extensive studies on various aspects of self-driving tourism, including scenic byway planning, accessibility measurement, and spatial behavior patterns. However, there is still a need for further research to explore the correlation characteristics and the coordinated relationship between scenic byway network accessibility and self-driving tourism. This paper focused on Western Sichuan as the study area and employed spatial design network analysis, GIS spatial analysis, and social network analysis models to assess the level of scenic byway accessibility and examine the characteristics of self-driving tourism behavior in the region. In addition, this study employed spatial econometric methods to empirically investigate the impact of self-driving tourism spatial behavior on scenic byway accessibility and the resulting spatial spillover effects. By integrating these analytical approaches, the research aimed to provide valuable insights for regional tourism transportation planning and the development of self-driving tourism routes in the area. The findings of this study will contribute to a better understanding of the relationship between self-driving tourism and scenic byway accessibility, offering practical implications for the optimization of tourism transportation networks and the enhancement of self-driving tourism experiences.

3. Materials and Methods

3.1. Study Area

The Western Sichuan region examined in this study encompasses the geographical area outlined in the "Overall Plan for National Highway 317/318-Sichuan-Tibet World Tourism Destination (Sichuan Section)". The study area specifically includes three counties within Chengdu City, namely Qionglai, Dujiangyan, and Wenjiang, as well as eight counties within Ya'an City, namely Yucheng, Mingshan, Yingjing, Tianquan, Hanyuan, Shimian, Baoxing, and Lushan. Additionally, it encompasses the entirety of Garze Tibetan Autonomous Prefecture and Ngawa Tibetan and Qiang Autonomous Prefecture (Figure 1).

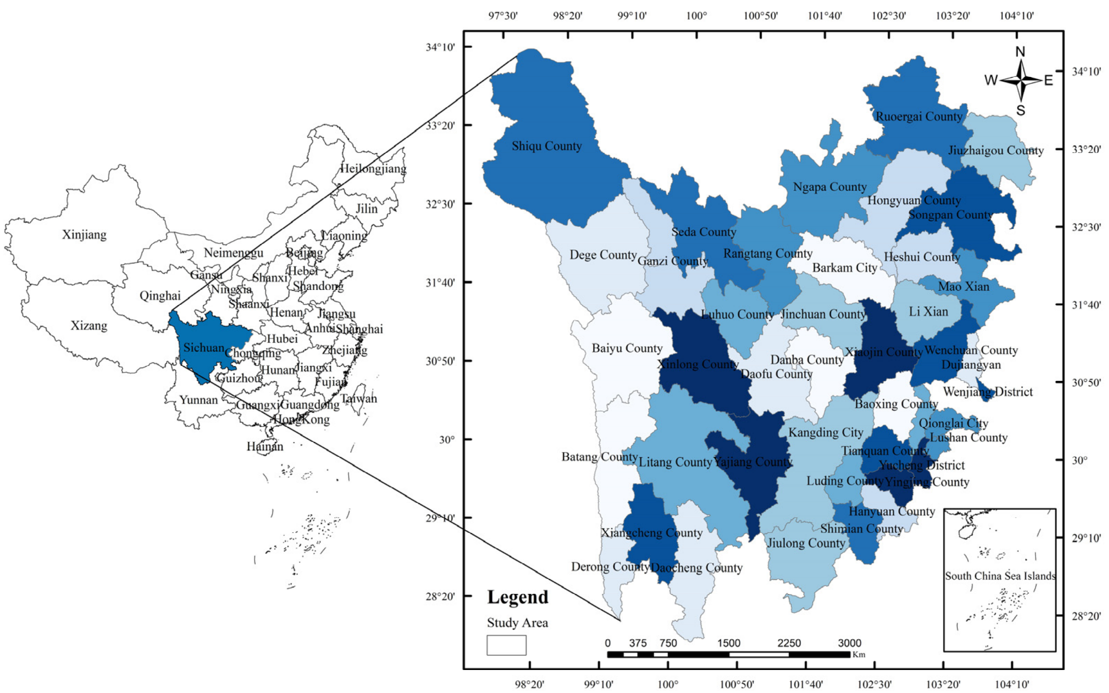


Figure 1. The geographical location of Western Sichuan.

Western Sichuan has abundant tourism resources, including several world natural and cultural heritage sites, biosphere reserves, geological parks, and intangible cultural heritage. Landmarks such as Giant Panda National Park, Jiuzhaigou, Mount Gongga, and Shangri-La are world-class tourist attractions and highly favored destinations for self-driving tourists in China. This region serves as a vital link between Sichuan Province and Tibet, characterized by a wide range of elevations spanning from over 500 m to over 7500 m. Notably, it boasts diverse terrain and landforms and a well-preserved ecosystem and represents the most comprehensive area in the Northern Hemisphere in terms of the vertical distribution of plant species. Furthermore, it possesses abundant and distinct resources, making it the most intricate and diverse high-mountain ecosystem corridor globally. Additionally, it stands as the oldest pathway for ethnic migrations, a trade route facilitating cultural integration, and an area teeming with natural and cultural heritage sites. National Highway 317/318, which traverses this area, holds significant importance as it serves as a crucial route leading to Tibet. Renowned for its picturesque landscapes, rich cultural heritage, and abundant resources along its path, this highway has earned the reputation of being the "scenic byway for Chinese people" and is the most favored self-driving route in China. Consequently, the Western Sichuan region has emerged as a highly sought-after destination for self-driving tourists within China.

3.2. Data Sources

There are five airports in the research area, all of which are located at an altitude of over 3000 m and are classified as high-altitude airports, primarily for general aviation purposes. In terms of railways, the region is currently only served by the under-construction Sichuan-Tibet Railway. Consequently, tourism activities in this area are primarily reliant on road transportation.

The road vector data utilized in this study for the study area is derived from OpenStreetMap, a publicly accessible and collaborative mapping platform. To ensure data accuracy and reliability, the obtained road data undergoes meticulous topological relationship checks and editing modifications. Through manual interpretation, the data is combined and cleaned, ensuring the generation of a comprehensive road network specific to the study area. This cleaning process involves the removal of empty values, interchanges, disconnected lines, and duplicate features. The resulting road network represents the required infrastructure for the study. Figure 2 provides the scenic byways network within the Western Sichuan region.

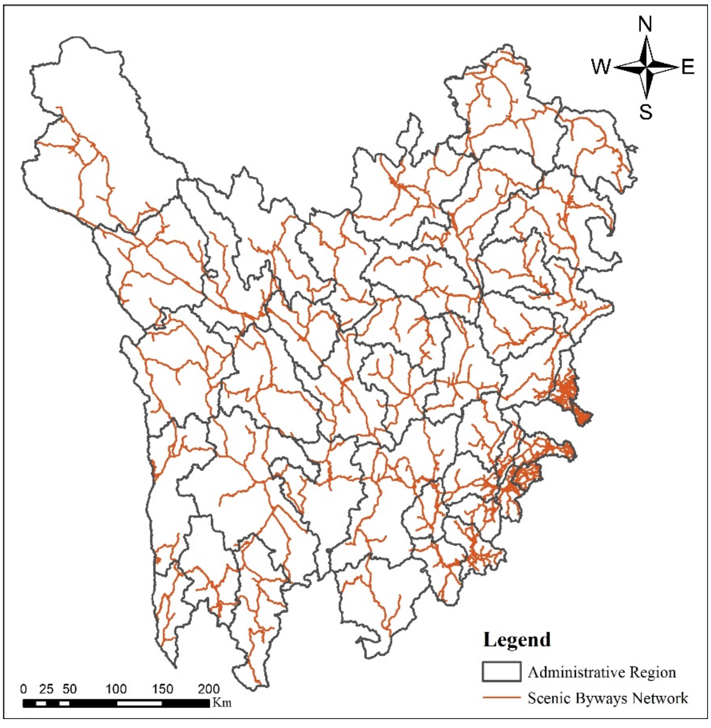


Figure 2. The scenic byways network in Western Sichuan.

The scenic byway network nodes are classified into three categories based on their attributes: tourism resource nodes, transportation-related nodes, and socio-economic and comprehensive tourism service nodes. Tourism resource nodes, classified according to "Classification, Investigation, and Evaluation of Tourism Resources" (GB/T 18972-2017, [61]), are primarily divided into natural resource nodes and cultural resource nodes. Tourism resource nodes are the core tourist attractions in the region, capable of attracting and generating tourism trips, providing various self-driving and recreational activities, and driving regional tourism economic and social benefits.

Transportation-related nodes serve self-driving tourism and encompass three major categories: automobile service nodes (gas stations, charging stations, vehicle rescue points, etc.), transportation facility service nodes (parking lots, long-distance bus stations, etc.), and road-related facility nodes (service areas, toll booths, etc.).

Socio-economic and comprehensive tourism service nodes include locations of tourist cities, central towns, tourist towns, and tourist characteristic villages, as well as self-driving camping sites, observation platforms, and other tourism service facilities.

To gather textual data for the travelogues, the Mafengwo website was selected as the primary source. Mafengwo is widely recognized as one of the most popular travel websites in China. Python web scraping techniques were employed to extract the travelogue text data from the Mafengwo website. The data collection process involved scraping travelogue texts related to Sichuan Province, with travel dates ranging from 1 January 2000, to 1 April 2022. In total, 7863 travelogues were collected.

The collected travelogues were imported into an Excel spreadsheet, which included essential information such as the travelogue title, author, place of origin, departure time, travel duration, travel companions, and the main text content. While big data techniques facilitated the rapid collection of a large sample, it was necessary to address certain issues in the collected data, such as duplicates and blank entries. Therefore, data filtering was performed.

The data filtering rules were as follows: (1) Exclude travelogues with multiple destinations that do not focus on self-driving tours in Western Sichuan; (2) Exclude travelogues that only provide information about scenic spots or promote hotels, guesthouses, or travel agencies, as well as those with mostly pictures and minimal text content; (3) Exclude travelogues with missing travel itineraries; (4) Merge serialized and duplicate travelogues.

By applying these filtering rules, travelogues specifically related to self-driving tours in Western Sichuan were isolated. Additionally, travelogues with missing data and duplicates were eliminated, resulting in a total of 4712 valid travelogues. Finally, from each travelogue text, self-driving travel chains were manually extracted. Travelogues with incomplete travel routes that primarily focused on a single destination were removed, leaving a final count of 2411 self-driving travel chains.

3.3. Research Methods

3.3.1. Accessibility Calculation

In terms of accessibility measurement indicators for scenic byways, this study adopted the proximity measure from the sDNA (spatial design network analysis) model [26]. Proximity represents the ease or difficulty of access compared with the rest of the road network within a given search radius. Road networks with high proximity tend to have higher accessibility and centrality, making them more attractive for regional transport flow. The description and calculation method are as follows.

$$NQPD(\mathrm{x}) = \sum_{y \in R_X} \frac{(W(y)P(y))^{nqpdn}}{d_M(x,y)^{nqpdd}} \tag{1}$$

In the formula: $W(y)$ represents the weight of chain y, $P(y)$ represents the weight of node y within the search radius R. This study conducts continuous analysis, so $P(y) \in [0,1]$. $d_M(x,y)$ represents the shortest topological distance from node x to node y. $nqpdn$ and $nqpdd$ are often taken as 1 for the analysis radius.

Node accessibility refers to the level of smoothness in the regional scenic byway system and reflects the ease of reaching each node within the scenic byway network. A smaller value indicates better node accessibility. The formula used to calculate node accessibility is as follows.

$$K_i = \frac{\sum d_{ij}}{n} \quad (2)$$

In the formula: $\sum d_{ij}$ represents node accessibility, and n represents the total number of nodes.

3.3.2. Social Network Analysis (SNA)

Social network analysis is an important analysis method used to describe the overall morphology and structure of the self-driving travel chain network. The structure of the self-driving travel flow network is composed of destination nodes for self-driving trips. Social network analysis methods are applied to analyze the importance of nodes in the self-driving travel network [62]. Based on the study of the spatial patterns in self-driving travel, social network analysis methods are applied to analyze various indicators such as the importance, centrality, structural holes, and core–periphery structure of self-driving travel nodes. This analysis aims to further understand the relationships between self-driving travel nodes and the basic characteristics of the self-driving travel chain network.

1. Centrality

Degree centrality (C_A) represents the number of nodes directly connected to a specific node in the network. A higher number indicates a closer connection between the node and others, primarily calculated by counting the number of connections between a node and other nodes in the network. Betweenness centrality (C_B) represents the number of shortest paths that pass through a node, reflecting its intermediary role in the network. A higher betweenness centrality indicates stronger control and mediation ability over other tourism nodes in the network. Closeness centrality reflects the proximity between a node and other nodes in the network. A higher closeness centrality indicates shorter paths from the node to all other nodes, indicating less dependence on other nodes. Outward closeness centrality ($C_{c,out}$) reflects a node's diffusion capability, while inward closeness centrality ($C_{c,in}$) reflects a node's aggregation capability.

2. Structural holes

Structural holes represent areas in the network structure where there are no connections between nodes, indicating fragmented regions. Structural holes can reflect competitive relationships. In a tourism route network, the higher the network density and the fewer the structural holes, the greater the competitive advantage of the nodes that span across the structural holes. Efficiency scale (ES) measures the non-redundant connections between the nodes in each travel chain and reflects the competitiveness of nodes in the network. A higher efficacy scale indicates greater competitiveness.

3.3.3. Bivariable Moran's I

The bivariate global Moran's I is used to explore the coupling relationship between the density of tourism resources and the density of sDNA measurement values at different scales. The calculation of the global Moran's I index, which assesses the overall spatial relationship between spatial features, is as Formula (3), and its value ranges from −1 to 1. A value greater than 0 indicates positive spatial correlation, and the closer it is to 1, the higher the degree of spatial clustering. A value of 0 indicates no spatial autocorrelation, indicating a random distribution.

$$I = \frac{n \sum_{n}^{i=1} \sum_{n}^{j=1} w_{ij} z_{xi} z_{yj}}{\sum_{n}^{i=1} \sum_{n}^{j=1} w_{ij} \sum_{n}^{i=1} z_{xi} z_{yj}} \quad (3)$$

In formula, I represents the bivariate Moran's I index, n represents the number of counties, Z_{xi} and Z_{yj} represent the standardized values of the kernel density of tourism resources and sDNA measurement values, respectively, and w represents the spatial weight matrix based on geographical distance.

3.3.4. Spatial Durbin Model

The spatial Durbin model and the spatial Durbin error model can not only measure the local area but also assess the influence of various road network variables in surrounding areas on the spatial distribution of tourism resources in the area through the multiplication of the weight matrix and explanatory variables. The spatial dependence effect in the spatial Durbin error model is captured within the error term, which describes the impact of the error shocks of neighboring regions on the explanatory variables [63,64].

The spatial Durbin model and spatial Durbin error model can not only measure the spatial average effects of different driving spatial behavioral variables and scenic byway network accessibility levels in the local area but also measure the spatial average effects of various self-driving spatial behavioral variables in surrounding areas and their level of scenic byway accessibility through the multiplication of the weight matrix and explanatory variables. The spatial Durbin error model further reflects the impact of error shocks from neighboring areas on the accessibility level and the influence on the explanatory variables [65].

Based on this, in this study, the spatial Durbin model and spatial Durbin error model are used systematically to explore the spatial spillover effects between the parameters of self-driving tourism flow and the level of scenic byway accessibility. In selecting the spatial weight matrix, following the research by Wang H.L. et al. [65], the expression for the geographical distance spatial weight matrix is as follows:

$$W = \begin{cases} \frac{1}{d^2 ij} & i \neq j \\ 0 & i = j \end{cases} \tag{4}$$

In the formula:

i and j represent the regions, counties, or cities;

d represents the Euclidean distance between region (district or city) i and region (district or city) j;

d^2 represents the squared Euclidean distance.

The formula for the spatial Durbin model (SDM) is as follows:

$$Y = \rho WY + X\beta + WX\theta + \varepsilon \tag{5}$$

The formula for the spatial Durbin error model (SDEM) is as follows:

$$\begin{gathered} Y = X\beta + WX\theta + \mu \\ \mu = \lambda W\mu + \varepsilon \end{gathered} \tag{6}$$

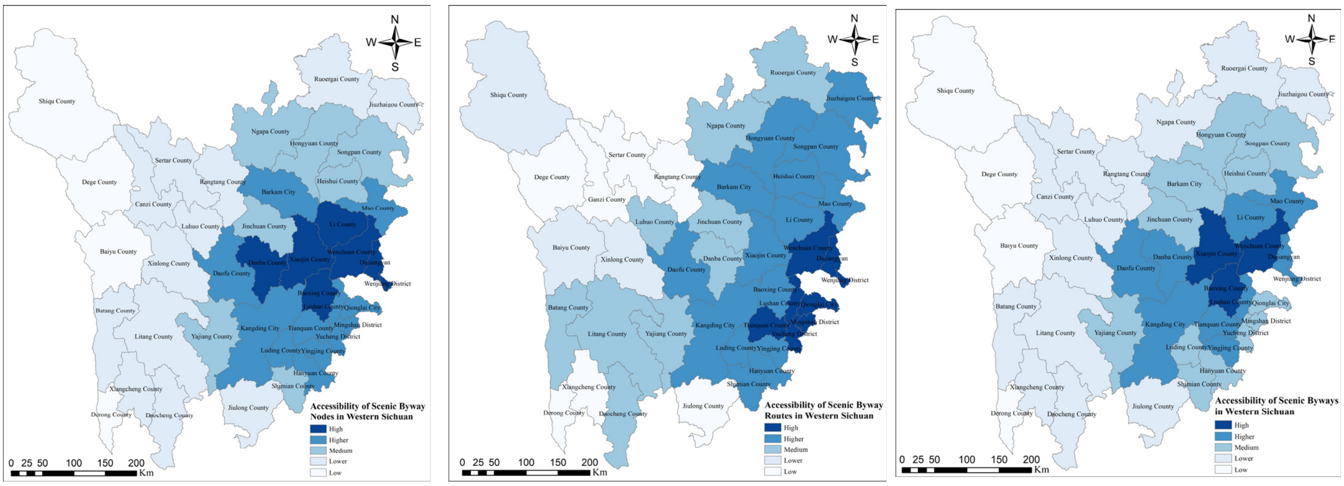
In the formula, the dependent variable is represented by K_{LX}, K_{JD}, and K_{FJD}, the explanatory variables are represented by $C_{c,in}, C_{c,out}, C_B$, and ES. W represents the spatial weight matrix ($N * N$, where N is the number of county units). θ, λ, and β represent the parameter vectors for the explanatory variables, μ represents the random error vector following a normal distribution, and ε represents the vector of random error terms.

4. Results

4.1. Calculation of Scenic Byway Accessibility

The evaluation of scenic byway accessibility in Western Sichuan encompasses both a local perspective and an overall perspective, as the scenic byway network exhibits a compositional relationship between these levels. The overall perspective focuses on assessing the quality of accessibility, which serves as an indicator of the development level of the entire scenic byway network in the region. Conversely, the local perspective emphasizes the evaluation of the accessibility of individual nodes, representing the quality of individual access. To effectively evaluate the accessibility of scenic byway routes and nodes in Western Sichuan, two distinct methodologies are employed: the sDNA (Spatial Design Network Analysis) model and the ArcGIS Network Analyst extension module. These approaches enable the calculation and measurement of both route and node accessibility, providing a comprehensive assessment.

To examine the spatial variations in scenic byway network accessibility, the spatial join tool in ArcGIS is utilized to aggregate calculations based on road network line features into county-level geographic units. As the accessibility of scenic byway nodes is derived from average travel time calculated through GIS network analysis, its numerical significance is inversely related to the accessibility obtained through sDNA calculations. Thus, it becomes necessary to normalize the global proximity of scenic roads and the accessibility of scenic byway nodes. To achieve this, expert scoring is employed, considering the sensitivity of route accessibility and node accessibility as equal. Both aspects are assigned weights of 0.5 each. The results are visualized in Figure 3 using the ArcGIS reclassification tool and the natural break classification method. This visualization facilitates the clear representation of the overall assessment of scenic byway accessibility, encompassing both route and node accessibility aspects.



(**a**) (**b**) (**c**)

Figure 3. Network accessibility level of scenic byways in Western Sichuan ((**a**) Node Accessibility, (**b**) Route Accessibility, (**c**) Scenic Byway Accessibility).

Results show that the overall accessibility of scenic byways in Western Sichuan exhibits a distinct spatial distribution pattern. It can be observed that there is a gradual decrease in accessibility from the core areas of Dujiangyan City and Wenjiang District, forming an "east strong, west weak, circle-layer distribution" pattern. This implies that the eastern regions of Western Sichuan have higher accessibility compared to the western regions, and the accessibility gradually decreases in a circular pattern from the core areas. Ngawa County Prefecture displays a "core–periphery" spatial structure, where Wenchuan County, Mao County, and Li County stand out with good accessibility and spatial agglomeration. These areas serve as the core regions with high accessibility, while the surrounding areas exhibit relatively lower accessibility. In Garze Prefecture, the overall accessibility is assessed as moderate, and it also demonstrates a "core–periphery" spatial structure. Kangding serves as the core area, with relatively higher accessibility, and the accessibility gradually decreases towards the periphery of the prefecture. Significant spatial differences in accessibility are observed across different regions, indicating a dispersed pattern. This means that there are notable variations in accessibility levels within Western Sichuan, with some areas having better accessibility and others having poorer accessibility. Overall, the level of scenic byway accessibility in Western Sichuan is evaluated as moderate. Only two counties (or districts) demonstrate a high level of accessibility, while the majority of areas have moderate or poor accessibility, accounting for approximately 65.85% of the total area.

4.2. Analysis of Self-Driving Travel Spatial Behavior on Scenic Byways

4.2.1. Overall Network Analysis

In this study, high-frequency tourism nodes (occurring more than 20 times) identified in the self-driving tourism flow network in Western Sichuan are considered as network nodes, and the flow trajectory of tourists between nodes represents the network relationships. A total of 2411 self-driving travel chains and 105 tourism nodes were selected. First, the directed self-driving routes between each pair of nodes were obtained by traversing the data to represent the self-driving tourism flow network in Western Sichuan. For example, if there is a one-way flow from node A to B, it is represented by the number 1, while if there is no flow from B to A, it is represented by the number 0. This information was used to construct a weighted directed matrix of 105 × 105 in size. Ucinet was used to construct the network structure diagram of the self-driving tourism nodes in Western Sichuan based on travelogue data, as shown in Figure 4, where the arrows represent the direction of tourist flow.

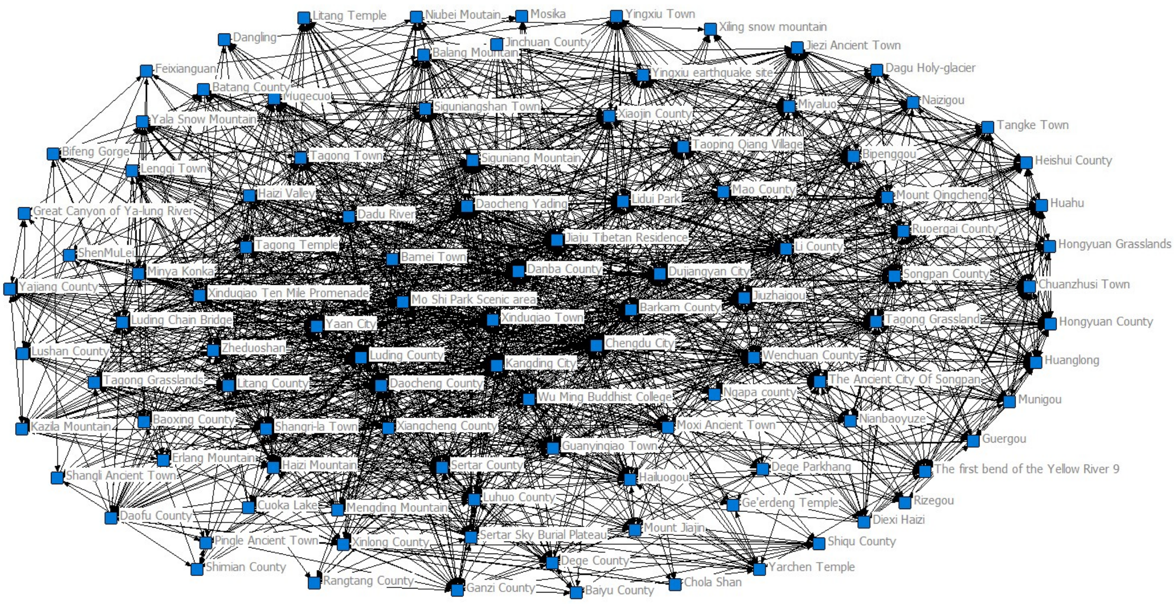


Figure 4. Network structure diagram of self-driving tour nodes in Western Sichuan.

Based on the calculation of relevant indicators for the self-driving tourism flow network in Western Sichuan, the following observations can be made:

(a) Overall Density and Clustering Coefficient: The overall density of the tourism flow network is 0.233, indicating a relatively low density. The clustering coefficient is 0.423, suggesting a higher level of clustering within the network.

(b) Coverage and Connectivity: The theoretical number of tourism flow paths in the network is 11,025, but only 2638 paths were observed in reality, accounting for 23.93%. This indicates that the coverage of the network is extensive but relatively concentrated in a few core cities. The network exhibits a low level of connectivity and weak links between nodes and towns.

(c) Degree Centrality: The outward degree centrality is 85.41%, the inward degree centrality is 83.65%, and the intermediate degree centrality is 26.83%. The higher outward degree centrality indicates an imbalance in the overall network structure, with significant aggregation and diffusion effects of core tourism nodes. The diffusion effect is better than the aggregation effect, and there is a clear spatial clustering trend in the network. Most nodes have one-way tourism connections, and there are several core nodes in the network.

(d) Intermediate Degree Centrality: The relatively low value of the intermediate degree centrality suggests that most nodes are connected to only a few core nodes in terms of tourism flows. These nodes hold strong control over the tourism connections of other districts and counties. However, such nodes are relatively few, indicating a weak overall transit capacity in the self-driving tourism flow network in Western Sichuan. Transfers require the aggregation and diffusion of multiple intermediate nodes, which are generally the core nodes in the network structure. This indicates a core–periphery structure in the network.

In summary, the self-driving tourism flow network in Western Sichuan has a low density and a loose overall network structure. It exhibits a high clustering coefficient and relatively short average path length, indicating a small-world phenomenon. The network structure shows an imbalance with significant aggregation and diffusion effects of core tourism nodes. Most nodes have one-way tourism connections, and there are a few core nodes that hold strong control over the tourism connections. The network exhibits a core–periphery structure.

4.2.2. Self-Driving Tourism Network Centrality Analysis

Centrality analysis was conducted on network nodes to quantify and evaluate the status of self-driving tourism nodes within the structure of the self-driving tourism network. Three major indicators, namely degree centrality, closeness centrality, and betweenness centrality, were calculated for the self-driving tourism flow network in Western Sichuan. The centrality indicators exhibited relatively high variance values, indicating the presence of significant network imbalance.

Degree centrality, which encompasses outward degree centrality and inward degree centrality, is utilized to assess the proximity of a self-driving tourism node to other nodes within the self-driving tourism network. Outward degree centrality reflects the node's external connections with other nodes, while inward degree centrality represents its internal connections. The average value of inward and outward degree centrality was calculated to be 25.12, indicating that, on average, each of the 105 self-driving tourism nodes in the network exhibited diffusion or aggregation relationships with approximately 25.12 other tourism nodes within the Western Sichuan self-driving tourism flow network.

Closeness centrality, an indicator of the proximity between self-driving tourism nodes, encompasses outward closeness centrality ($C_{c,out}$) and inward closeness centrality ($C_{c,in}$). $C_{c,out}$ represents the comprehensive measure of the difficulty for tourists to reach other self-driving tourism nodes from a specific node, while $C_{c,in}$ measures the difficulty for tourists from other self-driving tourism nodes to reach the specific node. The calculation results of closeness centrality are presented in Figure 5. The node with the highest closeness centrality is Chengdu, with an outward closeness centrality value of 99.048. Upon comparing the values of inward and outward centrality, it is observed that outward centrality generally surpasses inward centrality. Notably, Xiangcheng County, Dujiangyan City, Seda County, Danba County, and Luding County exhibit the largest disparities between inward and outward centrality values, with absolute differences of 12.105, 7.128, 6.899, 6.233, and 5.559, respectively. Approximately 57.14% of the self-driving tourism nodes function as outward-oriented nodes, indicating that the overall self-driving tourism flow network in Western Sichuan is predominantly characterized by outward-oriented tourism connections.

Betweenness centrality assesses the control capability of self-driving tourism nodes in their interactions with other nodes within the network. It serves as a valuable complement to degree centrality and closeness centrality, validating the results obtained from the node centrality analysis mentioned earlier. The calculation results of betweenness centrality are depicted in Figure 6. The total sum of betweenness centrality for each self-driving tourism node in the study area is 8463.998. However, the sum of betweenness centrality for the top ten self-driving tourism nodes amounts to 5531.259, accounting for 65.34% of the total. This indicates significant disparities in betweenness centrality within Western Sichuan, with the majority of tourism connections being facilitated by the top ten ranked self-driving tourism nodes. This concentration of control may not be conducive to the coordinated development of regional transportation and tourism. Chengdu exhibits notably higher betweenness centrality compared to other cities in the province, highlighting its core position within the overall network and its close tourism connections with other nodes. Kangding County, Danba County, Barkam County, and Jiuzhaigou County also play significant roles as tourism cores, tourism distribution centers, and secondary tourism cores and distribution centers within the network. Among the self-driving tourism nodes, only 16 counties possess a betweenness centrality exceeding 100, accounting for 15.23% of the total. Approximately 57.14% of the betweenness centrality values fall within the range of 10 to 100, indicating that most nodes possess a moderate level of control capacity. Additionally, there are 29 nodes with a betweenness centrality below 10, indicating a relatively weak global control capacity.

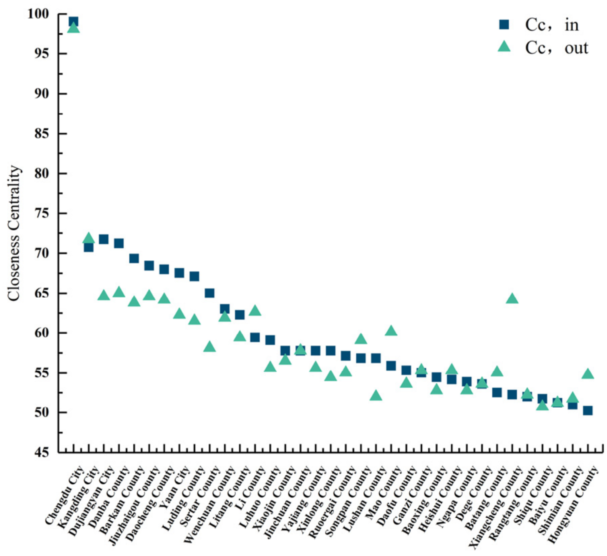


Figure 5. The node closeness centrality of self-driving tourism in Western Sichuan.

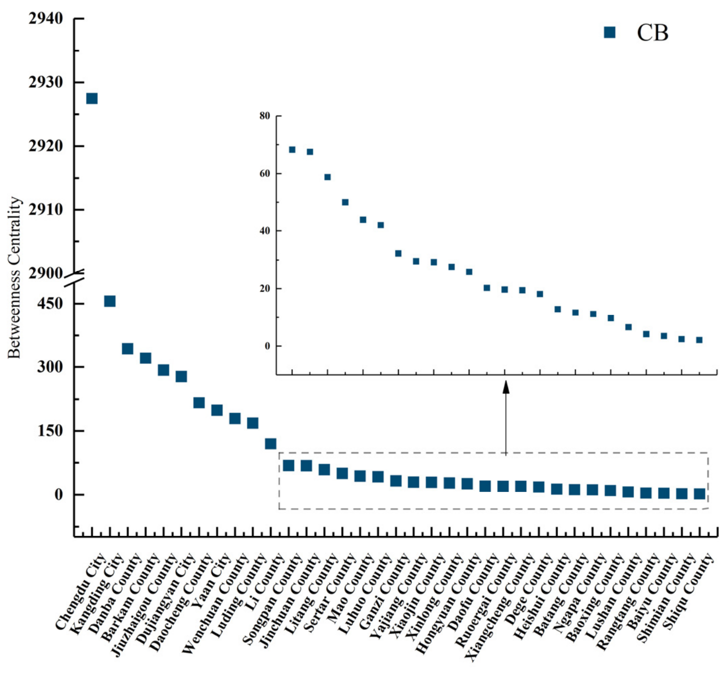


Figure 6. The node betweenness centrality of self-driving tourism in Western Sichuan.

In summary, (1) Chengdu, Kangding, Dujiangyan, Danba, Barkam, Jiuzhaigou, and other areas are the core nodes of the scenic byway network in Western Sichuan. These places are the most renowned tourist nodes in Western Sichuan, known for their convenient transportation, well-developed tourism infrastructure, and high tourist traffic, making them popular destinations in the region. (2) The distribution of nodes in the scenic byway network in Western Sichuan is uneven, with tourism flows in the region primarily controlled by a few core nodes. In self-driving tourism, tourists disperse and converge through these core nodes.

4.2.3. Node Structural Characteristics Analysis

Structural holes in the self-driving tourism network structure in Western Sichuan represent the relationships between different nodes, reflecting the status of each node within the network. By employing the structural hole model to calculate the structural hole indicators for self-driving tourism nodes in Western Sichuan, as depicted in Figure 7, we can gain insights into the network characteristics. The results reveal that counties under Chengdu City, Kangding City, Barkam County, Dujiangyan City, and Danba County exhibit relatively higher efficacy scale (*ES*), efficiency (*EF*), and lower constraint (*CT*). This suggests that these regions located at the center of the network serve as bridges and exhibit strong autonomy in tourism development, with a high level of tourist attraction.

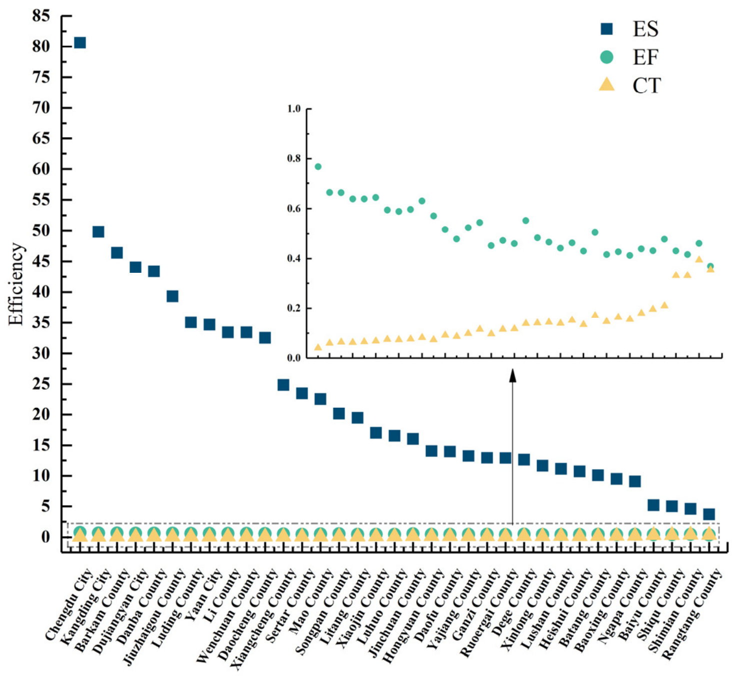


Figure 7. Structural hole analysis of self-driving tourism in Western Sichuan.

On the other hand, Ngawa County, Baiyu County, Shiqu County, Shimen County, and Rangtang County have relatively lower efficacy scale and efficiency, indicating fewer effective connections. Tourism development in these peripheral areas is constrained, and tourist attractions face a disadvantage in attracting visitors. From Figure 7, we can see that Barkam County is an important transportation node, serving as an intermediate node connecting other areas. It is relatively far from other nodes in terms of transportation, lacking alternative tourism towns and large scenic spots along this distance. Therefore, the control capability of transportation conditions on the overall self-driving tourism flow is much greater than the attractiveness of tourism resources. Visitors must first consider the service facilities of the transportation node upon arrival.

Within the self-driving tourism flow network, cities and towns located within Chengdu and Ya'an enjoy several advantages. Firstly, they benefit from relatively short distances between each other, facilitating convenient travel. Additionally, these areas boast comprehensive supporting facilities, ensuring a seamless and comfortable experience for tourists. Moreover, they possess strong scenic byway accessibility, allowing for easy exploration of various attractions. Furthermore, a larger number of nodes within Chengdu and Ya'an exhibit structural hole advantages, indicating a higher level of network openness and autonomy. This abundance of structural holes provides ample opportunities for small groups to explore diverse routes, promoting decentralization and flexibility in selecting self-driving tourism nodes.

4.3. Bivariate Global Autocorrelation Tests

The spatial Durbin model and the geographically weighted regression model are used to study the spatial spillover effects and spatial non-stationarity of variables in different geographical locations. They effectively analyze global average effects and local spatial heterogeneity. Therefore, before constructing global and local regression models, spatial effect tests are necessary. Moran's I index is commonly used to perform spatial autocorrelation tests on variables, s, which reflect the significance of the spatial distribution differences of the variables.

Prior to using spatial econometric models to measure the spatial relationship between scenic byway accessibility and self-driving spatial behavior, the bivariate global Moran's I index was applied to reveal the global spatial correlation patterns between the two variables. Geoda V1.20 spatial econometric software was used to calculate the bivariate global Moran's I index for county-level units in the study area. The results are shown in Table 1, where all variable parameters passed the significance level test, and the Euclidean distance threshold for adjacent county units was 144.248 km. The bivariate Moran's I index for inward closeness centrality and road accessibility was 0.108, while, for outward closeness centrality, it was 0.124. For node accessibility and overall accessibility, the bivariate Moran's I index increased to 0.115 and 0.129, and 0.149 and 0.161, respectively. This indicates that there is a positive spatial correlation between outward closeness centrality and scenic byway accessibility, and it is statistically significant at least at the 5% level. It was also observed that, compared to road accessibility, node accessibility and scenic byway accessibility had a more pronounced mutual influence on inward closeness centrality, showing a significant "resource-node orientation" feature.

Table 1. Bivariate global Moran index results.

	Outward Closeness Centrality	Inward Closeness Centrality	Betweenness Centrality	Efficacy Scale
scenic byway route accessibility	0.124	0.108	0.164	0.220
scenic byway node accessibility	0.149	0.115	0.305	0.303
scenic byway global accessibility	0.161	0.129	0.293	0.314

The Moran's I index of betweenness centrality with route accessibility, node accessibility, and global accessibility are 0.164, 0.305, and 0.293, respectively, showing an inverted "V"-shaped pattern. These values were statistically significant at least at the 5% level, indicating clear overall spatial dependence and correlation characteristics. Therefore, spatial effects cannot be ignored when studying the spatial relationship between the accessibility level of scenic roads and the spatial behavior of self-drivers in Western Sichuan.

4.4. Spatial Durbin Models Empirical Analysis

The empirical analysis using the spatial Durbin model reveals a significant spatial relationship between the scenic byway accessibility level and self-driving spatial behavior in Western Sichuan. When studying the spatial relationship between the two variables, the presence of spatial spillover effects cannot be ignored. Using STATA 15 software as the computational platform, the spatial Durbin model was used to estimate and test the relationship between scenic byway accessibility level and self-driving development level. To compare the performance of different models, this study also used both the spatial Durbin model (SDM) and the spatial Durbin error model (SDEM) for the maximum likelihood estimation. Table 2 presents the empirical results obtained using the method of constructing spatial autoregressive models in STATA 15.

Table 2. Regression analysis of SDM model and SDEM model.

	Route Accessibility		Node Accessibility		Scenic Byway Accessibility	
	SDM	SDEM	SDM	SDEM	SDM	SDEM
$C_{C,in}$	0.941 **	0.919 **	−0.787 *	−0.759 *	−0.096	−0.088 *
$C_{C,out}$	−1.180 **	−1.087 ***	0.959 **	0.917 **	0.137	0.124
C_b	0.179 ***	−0.171 ***	0.137 **	0.169 **	0.032 **	0.038 *
ES	0.961 ***	0.836 ***	−0.144 *	−0.173 *	0.224 ***	0.222 **
W * $C_{C,in}$	6.331	2.160 *	−20.109 ***	−18.178 ***	−10.944 **	−10.058 **
W * $C_{C,out}$	−9.951 **	−4.930 *	21.366 ***	19.760 ***	10.660 **	9.784 **
W * C_b	−1.658 **	−1.540 ***	2.778 ***	3.239 ***	1.371 *	1.427 **
W * ES	9.616 ***	7.172 ***	−4.548 **	−4.808 ***	−0.098	0.022 *
Log-L	37.942	36.625	36.012	36.468	43.401	43.421
R^2	0.771	0.758	0.813	0.826	0.838	0.882
AIC	−53.855	−51.251	−50.025	−52.935	−64.803	−64.843
BIC	−34.771	−34.136	−30.910	−31.821	−45.689	−45.728

In the table, ***, **, and * represent significance levels at 1%, 5%, and 10%, respectively.

From the results, it can be observed that the natural logarithm of the likelihood function (log likelihood) of the spatial Durbin error model is generally higher than that of the spatial Durbin model. In addition, the Akaike information criterion (AIC) and Bayesian information criterion (BIC) values of the spatial Durbin error model are generally lower than those of the spatial Durbin model. Therefore, this study will continue the analysis based on the results of the spatial Durbin error model.

The spatial lag term alone cannot directly determine the magnitude of the spatial spillover effects. In order to further explore the spatial spillover effects between the specific parameters of self-driving spatial behavior and accessibility, this study decomposes the spatial effects of the main model. By using STATA's spatial effects decomposition, the direct, indirect, and total effects values are obtained. Table 3 shows the results of the spatial decomposition of the direct and indirect effects of the Durbin model.

Table 3. Direct effect, indirect effect, and total effect of SDM model and SDEM model.

		Route Accessibility		Node Accessibility		Scenic Byway Accessibility	
		SDM	SDEM	SDM	SDEM	SDM	SDEM
Direct effect	CC,in	0.791 *	0.919 *	−1.367 *	−0.759 *	−0.167	−0.088 *
	CC,out	−0.929 **	−1.087 ***	1.577 *	0.917 ***	0.206 *	0.124 *
	Cb	−0.136 ***	−0.171 ***	0.218 **	0.169 ***	0.0414 *	0.038 *
	ES	0.708 ***	0.836 ***	−0.274	−0.173	0.2234 **	0.222 **
Indirect effect	CC,in	1.799	1.998	−36.251 *	−16.815 ***	−12.0294 *	−9.303 **
	CC,out	−3.022 *	−4.560	38.624 *	18.277 ***	11.7254 *	9.050 **
	Cb	−0.515 *	−1.425 **	5.032 *	2.995 ***	1.5104 **	1.320 **
	ES	3.037 ***	6.633 ***	−8.168 *	−4.447 ***	−0.067	−0.020 *
Total effect	CC,in	2.590 *	2.917	−37.618 *	−17.573 ***	−12.1964 *	−9.391 **
	CC,out	−3.951 ***	−5.647 *	40.201 *	19.194 ***	11.9314 *	9.174 **
	Cb	−0.651 **	−1.596 ***	5.250 **	3.165 ***	1.5514 **	1.357 **
	ES	3.745 ***	7.469 ***	−8.443 *	−4.620 ***	0.156	0.202 *

In the table, ***, **, and * represent significance levels at 1%, 5%, and 10%, respectively.

5. Discussion

5.1. Scenic Byway Accessibility

According to the results of the scenic byway accessibility calculation in Western Sichuan (Figure 3), the overall scenic byway network in the region exhibits a "two-axis and four-belt" road network structure with a spatial pattern characterized by block aggregation and axial extension. The "two axes" are centered around Chengdu and consist of two main east–west development axes based on the National Highway 317 passing through Dujiangyan and Barkam and the National Highway 318 passing through Ya'an and Kangding. Based on the "point-axis" theory, Zhang et al. [8] conducted research on the spatial system of tourism corridors in this region from green space ecological systems, spatial structure systems, and transportation accessibility systems and also reached the similar conclusions.

The regions traversed by the "two axes and four belts" are characterized by high values of closeness and betweenness (Figures 5 and 6), indicating firstly that these regions have good accessibility and centrality on a global scale, making them more attractive within the overall road network. Second, these areas have a higher level of network traversability, which accommodates a greater volume of traffic and is consistent with the actual high-level road network that carries a greater volume of long-distance traffic flows [55]. This confirms Li's [11] research, which points out that, from the perspective of tourism support elements, tourism transportation is the most important aspect of tourism public services. Highly accessible tourist attractions in Western Sichuan are mainly distributed along National Highway 317 and National Highway 318.

The analysis of local scale betweenness and efficiency indicates that the high accessibility areas exhibit a spatial structure characterized by "two cores and multiple nodes" overall. The "two cores" refer to the two core tourism cities in the research area, Chengdu and Ya'an. The "multiple nodes" include cities such as Kangding, Barkam, and Garze [8,9]. This conclusion is consistent with the spatial distribution characteristics of multi-core spatial structures in other regions [37,44].

5.2. Network Structure Characteristics of Self-Driving Tourism Flows on Scenic Byways

Overall, the network density of self-driving tourism flows in Western Sichuan is relatively low, indicating a loosely connected network structure. However, it exhibits a high clustering coefficient and relatively short average path lengths, indicating a significant small-world phenomenon in the self-driving tourism flow network in Western Sichuan. This suggests that self-driving tourism in Western Sichuan is characterized by a distant source market, longer travel times, and a preference for closed-loop tour modes. According to the "Research Report on Self-Driving Tourism of the Sichuan-Tibet Highway (2020)" [9] most tourists in this region choose travel modes that combine air travel or railway travel with self-driving. The majority of these travelers originate from Chengdu and rent or drive their own vehicles for the journey, and their travel duration typically ranges from 5 to 15 days. The source market is mainly composed of cities from China's economically developed regions, including the Beijing-Tianjin-Hebei urban cluster, the Yangtze River Delta urban cluster, and the Pearl River Delta urban cluster. These urban clusters are more than 1000 km away from the research area. The composition of tourist source areas is similar to that of Yunnan Province, which borders Western Sichuan [44].

5.3. Spatial Spillover Effects between Scenic Byway Network Accessibility and Self-Driving Spatial Behavior

Comparing the calculated scenic byway accessibility results with the model's self-driving spatial behavior parameters, the efficacy scale has a positive direct effect on scenic byway accessibility and a negative spillover effect. For every 1% increase in the efficacy scale index of local structural holes, the accessibility levels of the local area and adjacent areas will increase by 0.222% and −0.02%, respectively.

Regional self-driving competitiveness is an important factor that promotes the improvement of local scenic byway infrastructure and the potential increase in scenic byway accessibility [38]. Under the combined influence of spatial interaction theory and distance decay law, the improvement of regional self-driving competitiveness in the local and adjacent areas will relatively weaken the development advantages of scenic byway supporting services in adjacent areas. This, in turn, facilitates the improvement of local scenic byway planning and construction, effectively improving the local scenic byway accessibility level while inhibiting the improvement of scenic byway accessibility in adjacent areas. High efficacy scale regions refer to areas with competitive advantages in tourism. On the one hand, these regions have favorable tourism resources that support the improvement of regional transportation facilities. On the other hand, they generate a "siphon effect" on adjacent regions with lower transportation advantages [58].

Inward centrality has a positive direct effect and a positive spillover effect on the accessibility of scenic byways. For every 1% increase in local inward centrality, the accessibility levels of the local and adjacent areas will increase by 0.124% and 9.050%, respectively. On the other hand, the outward centrality has a negative direct effect and negative spillover effect on scenic byway accessibility. For every 1% increase in local outward centrality, the accessibility levels of the local and adjacent areas will decrease by 0.088% and 9.303%, respectively. Compared to outward centrality, high inward centrality regions are areas with a high influx of tourist flows, and they have a strong promoting effect on the development potential of accessibility in neighboring areas.

Betweenness centrality has a significant positive direct effect and positive spillover effect on the distribution of tourism resources. For every 1% increase in local betweenness centrality, the development potential of accessibility in the local area and adjacent areas will increase by 0.038% and 1.320%, respectively. This indicates that improving betweenness centrality is crucial for promoting comprehensive tourism. The improvement of local tourism intermediary capability and road service level contributes to the transition from "weak relationships" to "strong relationships" between regions. The presence of high-grade scenic byways, such as expressways and national highways, forms a strong tourism axis, transforming the spatial structure of scenic byways from "points" to "areas" [50]. This promotes the development of "comprehensive tourism" in the regions along the scenic byways in Western Sichuan and accelerates the integration of transportation and tourism [51].

6. Conclusions

6.1. Conclusions

This paper took the scenic byway network and self-driving tourism behavior in Western Sichuan as the research subjects. It constructed self-driving travel chains using travelogue texts from the Mafengwo website and analyzed the road network accessibility of the study area and the spatial behavior of self-driving tourism using mathematical statistics and complex network analysis methods. The main conclusions are as follows:

(1) The high accessibility areas of the scenic byways in Western Sichuan exhibited a spatial structure of "two axes and four belts". The coordination of accessibility among the "core–edge" regions varied significantly. While the core cities of Chengdu and Ya'an had relatively well-developed scenic byway accessibility, most areas in the region required further connectivity and optimization of the scenic byway road network. The accessibility of scenic byway nodes also followed a "core–edge" spatial structure, gradually decreasing outward from Chengdu and Ya'an. There was significant spatial variation in the accessibility level within the study area, with the majority of regions having moderate to low accessibility levels, accounting for approximately 65.85%.

(2) The spatial behavior network of self-driving tourism in Western Sichuan exhibited characteristics of relatively low overall network density, high clustering coefficient, and short average path length, indicating a significant small-world phenomenon. There was an observable imbalance in the indicators of each network node, with core nodes showing significant clustering tendencies. Nodes with strong outward centrality also exhibited strong inward centrality.

(3) The overall association pattern between the accessibility of scenic byways in Western Sichuan and the spatial behavior of self-driving tourism demonstrated clustering and dependence characteristics, with spatial effects playing a crucial role. There was a spatial spill-over effect between the level of scenic byway accessibility and self-driving tourism behavior. Regional efficacy scale had a significant positive direct effect and a negative spillover effect. For every 1% increase in local efficacy scale, it promoted a 0.222% increase in local accessibility and a −0.02% decrease in neighboring areas' accessibility. Local efficacy scale was an important factor in promoting the improvement of local scenic byway infrastructure and the potential growth of scenic byway accessibility. However, it had an inhibiting effect on improving accessibility in neighboring areas. Betweenness centrality had a positive direct effect on accessibility and a significant positive spillover effect. For every 1% increase in local betweenness centrality, it promoted a 0.038% increase in local accessibility and a 1.320% increase in neighboring areas' accessibility, strengthening the connectivity between regions from "weak relationships" to "strong relationships".

6.2. Implications

This paper presents a research framework for the accessibility of scenic byway networks and self-driving tourism behavior using GIS spatial analysis techniques and tourist digital footprint data. This framework combines traditional spatial quantitative analysis methods with complex network analysis, providing a new perspective for studying the interaction between transportation infrastructure and tourism behavior. In terms of theoretical research, the authors made the following efforts:

Firstly, in terms of research methods, traditional accessibility measurement methods are mainly conducted through weighted average travel time [30], gravity models [31], spatial syntax [32], spatial autocorrelation [37], and other approaches. Considering the compatibility of sDNA tools and GIS platforms, this paper uses network analysis and spatial design network analysis to break through the traditional spatial syntax axial line model, which defines the shortest path based on a single topological depth and adopts a measurement approach that combines "minimum angular distance" and "shortest Euclidean distance", providing new possibilities for measuring regional accessibility. The shift from a discrete spatial search radius to a continuous one allows for a change from the original binary values (0 or 1) to a continuous range from 0 to 1. This method not only improves computational accuracy but also supports subsequent research on the spatial behavior and spatial correlations of self-driving tourism, providing new insights into the integration of transportation and tourism research.

Secondly, in terms of research perspective, previous studies on the spatial behavior of self-driving tourists have mainly focused on analyzing aspects such as route patterns, spatial patterns of travel chains, and the overall spatial structure of networks [43,46]. There has been a lack of analysis on the relationship between the accessibility of transportation infrastructure and the spatial behavior of self-driving tourists. This paper explores a research approach that includes "scenic byway spatial patterns research—accessibility measurement—analysis of the spatial behavior network structure of self-driving tourism—correlation characteristics". It achieves this by using spatial Durbin models and geographic weighted regression models combined with analyses of centrality and structural holes. It considers both global and local perspectives, investigating the spatial spillover effects and spatial heterogeneity characteristics between scenic road accessibility and the spatial behavior of self-driving tourism.

Based on the above research and considering the practical needs of sustainable development in transportation and tourism in the research area, this paper proposes the following recommendations:

Firstly, promote the development of scenic byway construction from corridor development to a "regional perspective", creating a three-dimensional scenic byway network. In the context of self-driving tourism development in Western Sichuan, emphasis should be placed on improving the hierarchical structure of scenic byway networks and accelerating the development of road technology. Priority should be given to upgrading the technical standards of roads with high tourism demand and improving the construction of supporting service facilities. Efforts should be made to improve the existing radial layout of the scenic byway network, which is mainly centered around Chengdu. Emphasis should be placed on developing secondary cores in places such as Kangding, Barkam, Daofu, Jiuzhaigou, and Daocheng. These secondary cores should play a pivotal role and radiate outward, expanding the scenic byway network to cover the northwest and southwest regions of Graze Prefecture, as well as the northeast region of Aba Prefecture.

Secondly, create distinctive self-driving tourism routes, optimize tourism-related transportation facilities, and promote integrated regional transportation and tourism development. Establish premium self-driving tourism routes such as the "Most Beautiful Scenic Byways in China" along National Highway 317 and National Highway 318, the Giant Panda Ecotourism Scenic Byway, and the Gongga Mountain Scenic Byway Loop. In addition, it is important to accelerate the planning and construction of supporting transportation and tourism facilities, including service areas, self-driving campgrounds, observation platforms, scenic byway interpretation systems, distinctive hotels and guesthouses, museums, and unique traffic signs. This will facilitate the integration of transportation and tourism for comprehensive development.

Currently, this research remains at the level of single spatial factor analysis. In the future, the study can collect time-series data of the road network and self-driving activities in the Western Sichuan scenic byway region. By combining space–time voxel models and space–time cube models, multidimensional grid elements can be constructed to explore spatiotemporal evolution characteristics in-depth. Additionally, the impact of various control variables, such as road network morphology, economic foundation, and industrial structure, on the development of regional self-driving tourism can be investigated. By simultaneously applying the geographical detectors method to examine spatiotemporal evolution driving factors, a multidimensional approach can be utilized to explore the relationship between road networks and the spatial behavior of self-driving tourism.

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