JOURNAL OF TOURISM AND SERVICES
Issue 32, volume 17, ISSN 1804-5650 (Online)
www.jots.cz

Network Spatial Structure of Tourism Destinations from a Pole-Axis Perspective

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Received: 28 May 2025. **Revision received**: 25 August 2025. **Accepted**: 19 September 2025

Abstract
The spatial structure of tourism forms the foundation for strategic planning and regional coordination. Since the COVID-19 outbreak, Chinese tourists have increasingly adopted personalized and niche travel patterns, challenging traditional resource-oriented spatial models and generating new demands for adaptive destination planning. This study aims to mine tourist movement behaviour to reshape the spatial structure of tourism destinations and to integrate relevant theories, thereby providing theoretical insights and practical implications for spatial optimization and sustainable tourism development. Using travelogues from Ctrip, China's largest online travel platform, the study applies big data mining and social network analysis within the framework of pole–axis theory to examine Shanxi Province. This study is among the few that integrate social network analysis with pole-axis theory to analyse tourism spatial restructuring, thereby extending the application of pole–axis theory from a resource-oriented to a demand-oriented perspective and enhancing the practical utility of social network analysis findings for tourism planning. The results show that tourist behaviour reshapes spatial structures into a "dual-core, four zones, and eight clusters" pattern, which contrasts sharply with the government's planned "one pole, three zones, and eleven clusters" framework. The findings demonstrate a significant spatial mismatch, underscoring the need to shift from resource-oriented to demand-responsive strategies, and offering important implications for policymakers, destination managers, and scholars concerned with sustainable tourism and spatial planning.

Key Words: pole-axis theory; tourism destinations; online travelogue; spatiotemporal characteristics; network structure.

JEL Classification: L83, Z32

Reference: Song, L., Che Rose, R. A., & Mohd Zainol, R. (2026). Network Spatial Structure of Tourism Destinations from a Pole-Axis Perspective. *Journal of Tourism and Services*, 17(32), 28-36. https://doi.org/10.29036/mf51gy79

1. Introduction

The COVID-19 pandemic profoundly disrupted the global tourism industry, exposing systemic vulnerabilities and reshaping tourist behaviour (Castanho et al, 2021; Florek & Lewicki, 2022; Aziz & Long, 2022; Kang et al., 2024). Scholars have described these transformations as "new geographies in a locked world" (Korstanje & George, 2021) and an "immobility turn" that reconfigured mobility patterns and spatial interactions across destinations (Cairns & Clemente, 2023; Xu & M. Chen, 2025). In the post-pandemic "new normal," travellers have become more sensitive to health risks, prefer open spaces, and increasingly seek differentiated experiences rather than standardised mass tourism (Maingi et al., 2024; Darabos et al., 2024; Ruppenthal & Rückert-John, 2024). These shifts have disrupted established market patterns and reshaped spatial structures, producing uneven regional impacts (Liu et al., 2023; Bartoš et al., 2023) and echoing broader debates on socio-spatial asymmetries in tourism (Guia & Ayu Trisia, 2023).

China exemplifies these dynamics. Since 2023, trends such as "fast-paced multi-destination trips" (known as "special forces-style tourism"), "reverse tourism" to non-traditional destinations, "city walks," "concert tourism," and rural sports events like village football and basketball tournaments have gained remarkable popularity, in contrast to earlier mass forms such as "heritage tourism related to China's revolutionary past" (known as "red tourism") and "study tours." Contemporary tourist behaviour patterns reveal a distinct shift toward short-term, multi-destination travel and niche preferences (Hu & Chen, 2023). Against this backdrop, these emerging behavioural patterns pose new challenges for tourism planning and destination management (Kokash et al., 2024; Abou-Shouk et al., 2023; Hossain et al., 2022), underscoring the need for methodological tools that can capture such dynamics. In this regard, tourist flow research provides a critical lens for analysing tourist behaviour, particularly in investigating patterns of tourist movement to reveal the spatial structure of tourism.

Tourist flow refers to the temporary migration of people from their place of origin to a destination within a defined spatial and temporal scope, accompanied by corresponding capital movements (Korol, 2021). Owing to data limitations, early research primarily relied on surveys (Yang et al., 2007) and statistical records (Lew & McKercher, 2006), which were often restricted to small samples or specific regions. The advent of communication technologies has enabled the use of big data in tourism research (Martín Martín et al., 2023; Bacik et al., 2025). Social media data from Instagram and Twitter have been employed to examine destination image and tourist intentions (Marin et al., 2021; Ballester et al., 2023), while big-data approaches have also contributed to studies of demand forecasting, spatial distribution, and mobility patterns (Kolková & Ključnikov, 2021; Paül & Daniel, 2018; Türk et al., 2021). In parallel, the use of mobile signalling and Airbnb records has further advanced the field, enabling more detailed analyses of network structures and tourist flow communities (Encalada-Abarca et al., 2022; Hu et al., 2023; Aziz et al., 2024).

In China, with over 1.1 billion internet users and 548 million online travel bookers (CNNIC, 2024), the vast digital user base provides diverse data sources, such as User-generated content Flickr photos and online travelogues (Mou et al., 2020a; Liu et al., 2022), point of interest (POI) datasets (Wang et al., 2022; Guo & Liu, 2021), Baidu Index (Zhang & Yuan, 2022), and mobile signalling records (Shi et al., 2023) together provide a strong empirical foundations for investigating the spatiotemporal dynamics, mobility behaviours, demand intensity, and network structures of tourist flows. Nevertheless, although tourist mobility has been examined to construct network structures, most findings remain descriptive, with limited theoretical integration, and empirical applications have disproportionately focused on metropolitan hubs or mature destinations, while underdeveloped regions remain underexplored. Addressing these shortcomings, this study is guided by the research question of how tourist movement behaviour reshapes the spatial structure of tourism destinations in underdeveloped regions, and how this process can be examined in greater theoretical depth.

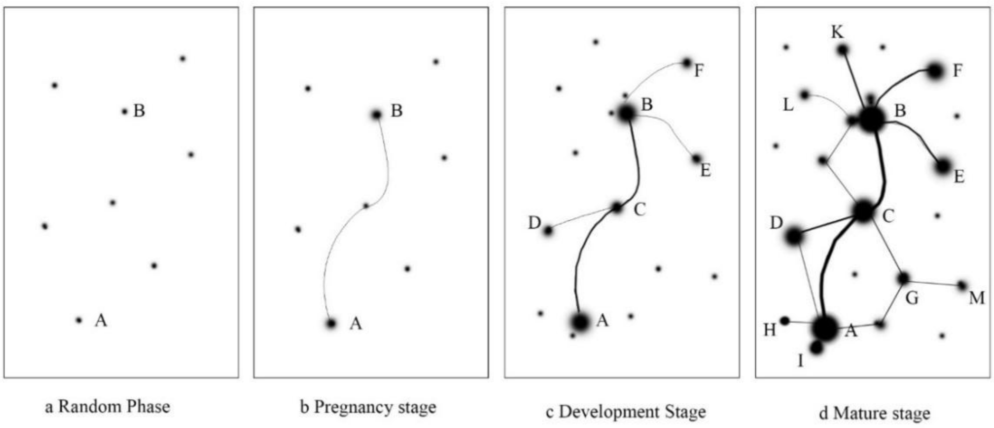
Shanxi Province provides an appropriate context for addressing this question. As one of the cradles of Chinese civilisation, it possesses an exceptionally rich concentration of historical and cultural resources, including UNESCO World Heritage Sites such as the Yungang Grottoes and Pingyao Ancient City. Yet, its long-standing dependence on the coal industry has constrained tourism development, positioning Shanxi as a resource-rich but underdeveloped destination (PGSX, 2021). In recent years, the provincial government has elevated tourism to a pillar industry and launched a spatial restructuring strategy centred on a "人-shaped" transport corridor with Taiyuan at its core, supported by the Yellow River, Great Wall, and Taihang Mountain tourism zones. This has produced a spatial pattern characterised as "one pole, 人-shaped corridor, three zones, and clustered development" (CTDSX, 2022). At the same time, evolving tourist behaviours are reshaping Shanxi's tourism landscape from the bottom up. For example, the release of the game Black Myth: Wukong in 2024 generated more than 10 billion online views linked to Shanxi tourism, revitalising interest in iconic sites and propelling lesser-known attractions such as Xiaoxitian in Xi County into record-breaking visitation (CTDSX, 2025). Shanxi thus represents a distinctive case where government-led spatial planning coexists with demand-driven restructuring, providing a critical context for examining how tourist behaviour reconfigures destination spatial structures.

To address this research problem, this study employs big data mining techniques to analyse tourist mobility patterns and uncover the tourism spatial structure of Shanxi Province. The analysis is guided by pole–axis theory, which derives from central place theory (Liu et al., 2024). Pole–axis theory reflects the objective regularities of socio-economic spatial organisation and the formation of spatial structures, and is widely regarded as an optimal framework for regional development (Wang et al., 2024). At the same time, it provides a natural interpretive framework for the network topology derived from tourist flow data, as both can be abstracted spatially into networks composed of nodes and edges (Lu, 2024; Benítez-Andrades et al., 2020). In this framework, nodes represent “poles” and edges represent “axes.” To the best of our knowledge, this is the first study to integrate pole–axis theory with social network analysis (SNA), employing metrics such as network density, centrality, structural holes, and cohesive subgroups to identify tourism poles, axes, and zones. This integration not only extends the application of pole–axis theory but also provides a quantitative framework for demand-driven spatial planning of tourism in underdeveloped regions.

2. Literature review

Tourism spatial structure reflects the spatial patterns of tourism activities and plays a critical role in regional tourism planning and development (Chen et al., 2023b). It is commonly conceptualized as a network composed of nodes and axes (Wang et al., 2023), which aligns with the pole-axis theory. This theory posits that economic centres first emerge as growth poles in advantageous locations. As they strengthen, their influence spreads along the axes, thereby promoting regional development (Lu, 2024), as shown in Graph 1. In the tourism context, “poles” usually refer to core destinations, while “axes” denote channels that facilitate the exchange of people and other elements, such as transportation corridors and travel routes (Wang et al., 2024).

Graph 1. **The evolution phases of the pole-axis system’s spatial structure.**



Source: modified by Song et al. (2025)

Based on this framework, Shi and Li (2003) identified three key contributions of the pole-axis theory to tourism research: tourism nodes enhance the radiating role of core cities, tourism axes extend

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the spatial reach of tourism development, and their interaction facilitates the optimization of spatial patterns. This logic not only clarifies the intrinsic mechanisms of tourism spatial structure but also provides a theoretical foundation for analysing it from a systematic "pole–axis–zone" perspective. Empirical studies further demonstrate its explanatory and planning utility across different scales and contexts, such as the "one pole, three axes, and four zones" pattern in Shanxi Province (Song et al., 2025), the "three poles-two axes-two secondary poles" in Beijing (Liu et al., 2024), the "one pole, two axes, and three zones" planning in Xima Village, Anhui Province (Wang et al., 2023), and the industry exhibited a "one main, one secondary" dual-centre pattern in Nanjing (Wang et al., 2024). Collectively, these cases highlight the central role of pole-axis theory in advancing research on tourism spatial structures.

However, most existing studies remain resource-oriented, typically focusing on officially designated scenic spots, cultural heritage sites, or settlements (Shi & Li, 2003; Wang et al., 2023; Wang et al., 2024), while paying limited attention to demand-side dynamics and tourist mobility (Liu et al., 2024). With the maturation of the tourism market and tourists' increasing pursuit of personalized, diversified, and experiential travel (Maingi et al., 2024; Kurar, 2021; Hu & Chen, 2023), resource-oriented approaches are no longer sufficient to guide tourism spatial structure (Song et al., 2025). This imbalance reveals a critical gap, although the pole–axis theory has been widely applied in regional planning and tourism development, yet its potential to interpret tourism spatial restructuring from a demand-side perspective, driven by tourist behaviour, has received insufficient scholarly attention.

Recent advances in big data provide a promising pathway to bridge this gap by incorporating behavioural evidence into spatial analysis (Bilan et al., 2024). Different data sources vary in their effectiveness for capturing mobility. POI data offer broad coverage and strong timeliness but provide limited insights into tourist flow characteristics (Wang et al., 2022). In contrast, mobile signalling, geotagged social media, and online travelogue can better track tourist trajectories (Hu et al., 2023; Encalada-Abarca et al., 2022; Mou et al., 2020a). However, the widespread application of mobile signalling data faces challenges due to data accessibility and high usage costs (Shi et al., 2023). Additionally, social media platforms such as Flickr and Instagram have low adoption rates in China, limiting the applicability of their data. By contrast, online travelogues are cost-effective, scalable, and spatially rich, providing a robust basis for analysing the spatiotemporal characteristics of tourist flows (Liu et al., 2022; Yi et al., 2024). Integrating online travelogues into research helps expand methodological approaches, compensate for the limitations of traditional data, and enhance the understanding of tourist mobility characteristics (Mou et al., 2020b).

With the continuous improvement of data sources, methodological advancements have enabled a more refined analysis of tourism spatial structures. Econometric models and Geographic Information Systems (GIS) remain valuable for quantitative assessment and spatial visualization (Türk et al., 2021; Wang et al., 2022; Shi et al., 2023), but they are limited in capturing dynamic inter-destination linkages (Park et al., 2020; Song et al., 2025). By examining the attributes of nodes (entities) and edges (relationships) (Benítez-Andrades et al., 2020), SNA introduces a relational perspective that complements these traditional approaches. It is particularly well-suited for exploring how patterns of tourist movement reshape the spatial structure of tourism systems, thereby uncovering relational dynamics that conventional models often struggle to capture (Gan et al., 2021; Mou et al., 2020b).

In summary, while the pole–axis framework offers a robust macro-level lens for examining tourism spatial structures, its applications have largely remained supply-driven. The growing availability of behavioural big data—particularly online travelogues—together with the relational strengths of SNA, creates new opportunities to bridge this gap. Integrating pole–axis theory with behavioural and network perspectives can thus deepen our understanding of how tourist movements restructure spatial configurations, providing critical insights for spatial optimization, destination competitiveness, and the sustainable development of regional tourism (Pejic & Milincic, 2024).

3. Methods

3.1 Data sources and tools

Major OTA platforms where Chinese tourists write travelogues include Ctrip, Tuniu, Tongcheng, Mafengwo, Meituan Travel, and Fliggy. In 2021, Ctrip led the market with a 36.3% share, rising to nearly 50% when combined with Qunar. Other platforms, including Meituan Travel (20.6%), Tongcheng (14.8%), and Fliggy (7.3%), together accounted for 92.9% of the domestic market (Red Star Capital Bureau, 2023). Given Ctrip's market dominance, high user activity, and large transaction volume, data from this platform is considered both representative and reliable, and has been widely adopted in tourism studies (Liu et al., 2022; Hou et al., 2019).

Ctrip hosts a "Travel Notes" section where users share their personal travel experiences. These travelogues can be searched and filtered using location-based keywords such as provinces or cities (Chen et al., 2023a). In this study, travelogues related to Shanxi Province were collected using Octopus Collector, a widely used visual web scraping tool that supports data extraction without requiring programming knowledge. Owing to its user-friendly interface and broad functionality, Octopus has been widely employed in academic research (Yi et al., 2024).

3.2 Data collection and processing

Data collection involves two steps. First, the data to be crawled needs to be preset on Ctrip.com. Second, the set URL (https://you.ctrip.com/travels/shanxi100056/s2-p1.html) is input into Octopus for Data Extraction and Collection. The specific data collection and processing process is as follows (Table 1). After data collection, A total of 2,670 travel notes related to Shanxi were retrieved and stored in the Excel database. Each entry included key structured fields such as title, username, content, publication date, travel duration, and travel expenses.

Following the methodology proposed by Chen et al. (2023a) and Mou et al. (2020b), the data processing phase included three key procedures: First, Data Cleaning: This step aimed to filter valid travelogues. After elimination and integration, 574 valid entries were retained for further analysis of temporal characteristics and tourist origins. Second, Attraction Extraction: The goal of this step was to identify representative tourist attractions mentioned in the travelogues. As a result, 359 entries with clearly identifiable destination nodes were extracted. Third, Matrix Construction: This step involved converting directional attraction nodes into a relational network matrix recognizable by UCINET 6, forming the basis for subsequent network analysis.

Table 1. **Relevant Technical Process**

Process	Step	Specific operations
Data collection	Keyword Search and Preliminary Filtering	The keyword "Shanxi" was entered in the "Travel Notes" section of Ctrip, and the results were "sorted by publication date".
	Data Extraction and Collection	The resulting URL was then imported into Octopus, which extracted all relevant travelogues published before the search date—March 27, 2024, in this study.
	Result	A total of 2,670 travel notes related to Shanxi were retrieved
Data processing	Data Cleaning	1. Integrated scattered travel notes published by the same traveller during the same trip period. 2. Eliminated duplicate entries, posts with unclear references to attractions, and filtered out invalid travelogues such as commercial promotions.

JOURNAL OF TOURISM AND SERVICES
Issue 32, volume 17, ISSN 1804-5650 (Online)
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		3. Verified the number of days spent in Shanxi for travel notes across provinces.
	Result	After processing, 574 valid data were obtained.
	Attraction Extraction	1. Manually recorded the names of attractions mentioned in each of the 574 original travelogues in the content. 2. Standardize the names of scenic spots, such as Shenlong Bay Wall Road and Jingdi Village Wall Road are different names for the same attraction. 3. Attractions belonging to the same scenic area within each processed travelogue were consolidated, for example, merging "Xuankong Temple" with "Hengshan Scenic Area." 4. Considering the representativeness of the network structure, after multiple attempts, those with visitation frequencies lower than 0.2% (fewer than 4 visits) were removed. 5. Only travelogues containing two or more distinct scenic areas were retained. 6. Classify the travel flow into directed nodes based on the visitation order, and count the visit frequency of each directed node.
	Result	After manual screening, In the end, 359 valid data entries remained, covering 74 nodes in Shanxi.
	Matrix Construction	Construct a 74*74 Origin-Destination (O-D) co-occurrence matrix based on directed nodes. Then, using the mean of the matrix as the threshold value, convert the co-occurrence matrix into a binary matrix.

Source: Composed by the authors based on the survey results

3.3 Data analysis

SNA, widely applied in sociology, economics, management, and geography (Hou et al., 2019), is used in this study to examine tourist mobility patterns and thereby uncover the spatial structure of tourism in Shanxi Province. Using UCINET 6.813, we calculate network density, centrality, structural hole metrics, and use convergent correlation (CONCOR) to analyse cohesive subgroups. The computational procedures follow Gan et al. (2021), who analysed the spatial network structure of an urban agglomeration's tourism economy, where centrality measures indicate node importance, structural holes identify bridging roles, and cohesive subgroups reveal tightly connected destination sets. These metrics enable the identification of tourism network structures driven by tourist flow patterns, forming the empirical foundation for the subsequent "pole–axis–zone" spatial structure framework. Network visualization is carried out with the Net Draw module integrated in UCINET.

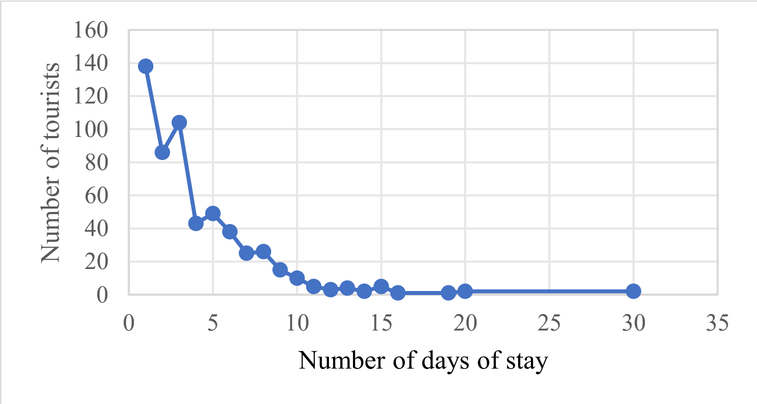
4. Results

4.1 Time distribution characteristics of tourist flows in Shanxi Province

4.1.1 Analysis of the length of stay of tourist flows in Shanxi Province

We collected 574 travelogues and categorized them by travel month and trip duration. Among them, 559 specify trip duration, and 540 mention the start date. Graph 2 shows that short-term tourism (less than five days) dominates Shanxi Province's tourist flow, accounting for 75.13%. Day-trippers make up 24.69%, likely due to local outings or Shanxi serving as a transit point. For example, a tourist from Shanghai in July 2023 reported a 14-day trip to the southern Taihang Mountains, spending just one day in Shanxi. Additionally, 2-day and 3-day tourists represent 15.38% and 18.6%, respectively, likely driven by weekend and short holiday trips from neighbouring provinces.

Graph 2. **Line chart of length of stay of tourist flows in Shanxi Province**

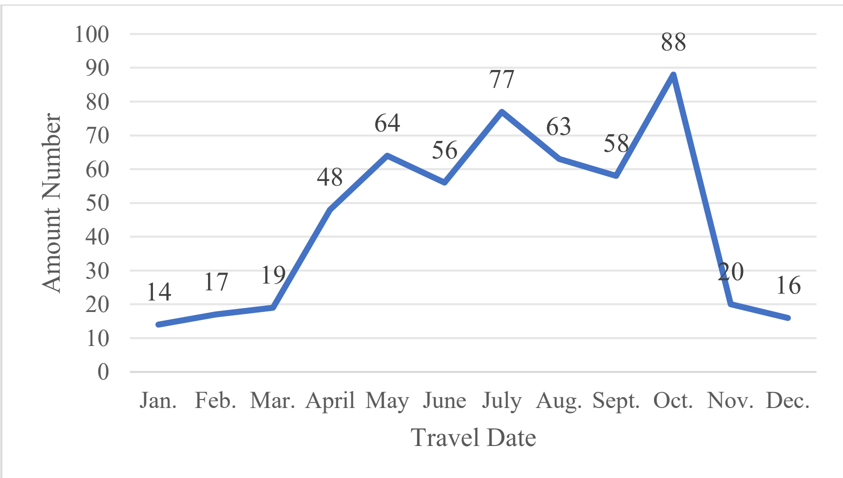


Source: Author.

4.1.2 Analysis of tourist flow seasons in Shanxi Province

Graph 3 shows that tourist visits to Shanxi Province peak from April to October, influenced by the climate and holidays. Shanxi's temperate monsoon climate offers blooming flowers and lush greenery during this period, making it the prime tourist season. Additionally, statutory holidays such as Qingming Festival, Labor Day, Dragon Boat Festival (each 3 days), and National Day (7 days) drive tourist activity. The extended National Day holiday explains the October peak, which accounts for 16.3% of visits. July (14.3%) and August (11.7%) also see high numbers due to the summer vacation and Shanxi's appeal as a "summer resort." Many tourists mention bringing children to Shanxi to witness history and to "escape the summer heat."

Graph 3. **Tourism season in Shanxi Province**



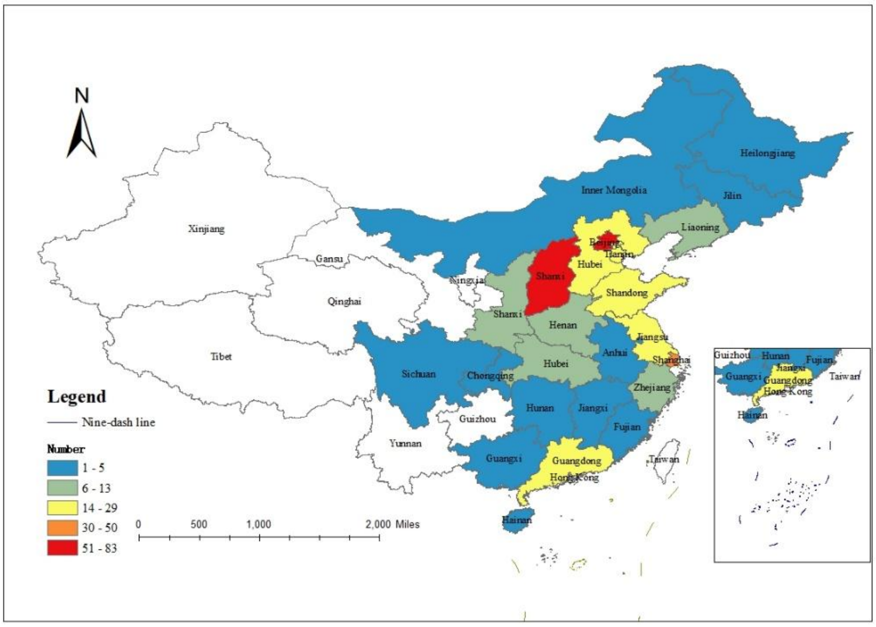
Source: Authors

4.2 Spatial characteristics of tourist flows in Shanxi Province

4.2.1 The spatial characteristics of tourism origin destinations in Shanxi Province

Of the 574 travelogues, 393 included origin destinations, with 391 originating from 24 provinces, municipalities, or autonomous regions (Graph 4). Beijing accounted for the largest share (21.23%), likely due to its economic development and proximity to Shanxi. Visitors from Shanxi ranked second (19.18%), while Shanghai ranked third with 50 travelogues. Notably, 58% of Shanghai visits occurred between 2019–2021, possibly driven by Shanxi's admission fee waivers for visitors from Jiangsu, Zhejiang, and Shanghai during the pandemic. Hainan, Jilin, and Chongqing had the fewest travelogues, with only one each. Western provinces showed minimal representation, likely due to distance and accessibility challenges.

Graph 4. **Distribution map of tourist source areas in Shanxi Province**

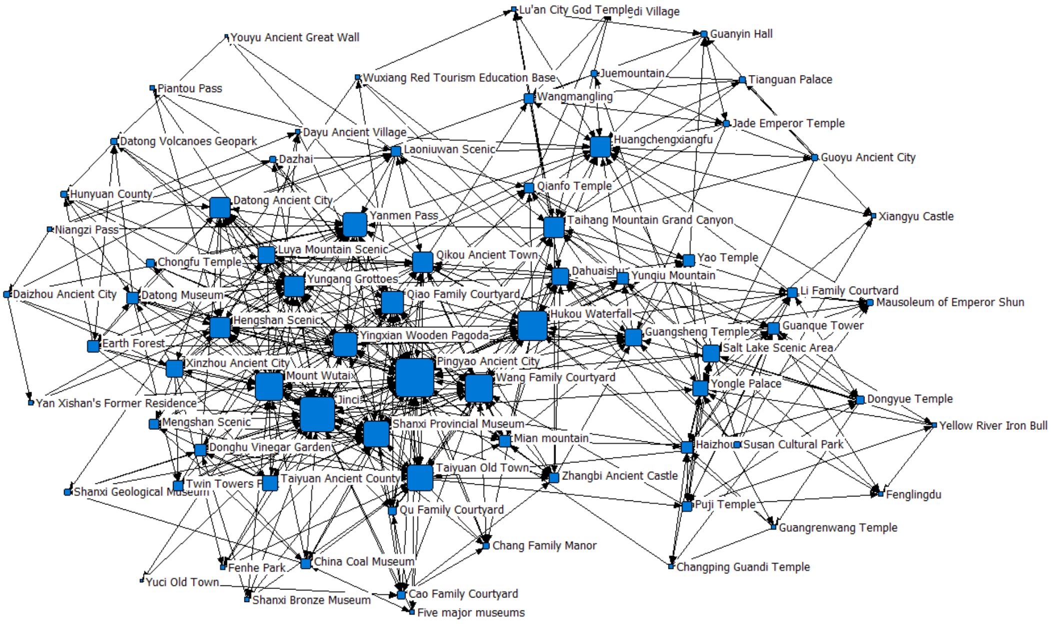


Source: Ministry of Natural Resources, 2019 China Map-Map Approval No. GS (2019)1822
No modification to the base map

4.2.2 Overall network structure analysis

Graph 5 shows that the 74 nodes form 593 connections, far below the theoretical maximum of 5402. The network density is 0.11, indicating that only about one-tenth of the nodes are interconnected, with most weak relationships. This highlights the need for enhanced cooperation and coordination between nodes.

Graph 5. **Shanxi Province tourist flow network structure**



Source: Authors

4.2.3 Centrality analysis

Centrality is the most critical measure in social networks, typically assessed using degree, closeness, and betweenness centrality. The specific results are shown in Table 4. Due to space limitations, only the top 20 attractions ranked by comprehensive value are listed here. For more details, please refer to the supplementary materials 1.

（1） Degree centrality

Degree centrality measures a node's central position in the network, with higher values indicating greater centrality. For directed matrices in tourist flow, degree centrality is divided into outward and inward measures. Nodes are categorized as gathering portals (outward < inward), diffusion portals (outward > inward), or core portals (both high) (Mou et al., 2020b).

The average centrality value for all nodes is 8.014, meaning each node connects to an average of 8 others. Inward centrality (36.086%) surpasses outward centrality (24.977%), indicating an overall imbalance. Pingyao Ancient City and Jin Ci rank highest, serving as tourism core portals for aggregation, transfer, and diffusion in Shanxi Province.

Attractions like Mount Wutai, Wang's Courtyard, Taiyuan Old City, and Hukou Waterfall exhibit higher outward than inward centrality, driving regional development through spillover effects. In contrast, Pingyao Ancient City, Shanxi Provincial Museum, Yungang Grottoes, and Mount Heng Scenic Area have higher inward centrality, suggesting a "central city effect" that may limit surrounding nodes' development. Jin Ci and Yanmen Pass have balanced inward and outward centrality, functioning as core hubs in their regions.

（2） Closeness centrality

Closeness centrality assesses how closely a tourism node connects with others based on distance, with higher values indicating stronger connections (Wang et al., 2020). In Shanxi, the distribution of closeness centrality mirrors degree centrality, with higher values concentrated in the northern and central regions. This indicates that the development level of tourist attractions in the central and northern regions of Shanxi Province is higher than in the southern region. The average inward and outward closeness centrality values are 41.1 and 29.487, respectively, suggesting that tourism nodes are not optimally connected.

Attractions like Pingyao Ancient City, Jin Ci, Wang's Courtyard, Shanxi Provincial Museum, and Hukou Waterfall exceed the average inward closeness centrality, reflecting high accessibility, convenient transportation, and strong interconnections. These destinations are well-positioned to receive information and serve as key hubs. In contrast, sites such as Niangzi Pass, Yuhuang Temple, Yellow River Da Tieniu, Guangren Temple, and Changping Guandi Temple show lower accessibility and weaker connections.

Outward closeness centrality highlights attractions like Niangzi Pass, Jin Ci, Pingyao Ancient City, Wang's Courtyard, and Hukou Waterfall for their strong external connections, facilitating better information dissemination and influence. However, sites such as Youyu Ancient Great Wall, Guanyintang, Fenglingdu, Jingdi Village, and Piantou Pass lag in external connectivity due to their remoteness.

Overall, Jin Ci, Pingyao Ancient City, Wang's Courtyard, Hukou Waterfall, and Mount Wutai emerge as dual-function hubs, excelling in both external communication and internal connectivity, solidifying their roles as key regional attractions.

（3） Between centrality

Betweenness centrality measures a node's control and dependence within a network, with higher values signifying stronger control (Gan et al., 2021). Pingyao Ancient City exhibits the highest betweenness centrality, underscoring its pivotal role in the network. It serves as a key interface for communication, information dissemination, and regional collaboration, exerting significant control over other nodes. In contrast, attractions like Niangzi Pass, Shanxi Bronze Museum, Yellow River Da Tieniu, and Piantou Pass are more dependent on major core cities and occupy weaker positions in terms of tourism development.

4.2.4 Structural hole

Structural holes assess the degree of homogeneous competition among nodes within a tourist flow network. Key indicators include energy size, efficiency, and constraints (Li et al., 2020). Research suggests that a higher EffSize value indicates lower network redundancy and greater efficiency, while lower constraint values signify higher levels of structural holes, reflecting enhanced competitiveness (Cui & Li, 2020).

As shown in Table 4, nodes such as Pingyao Ancient City, Jin Ci, Hukou Waterfall, Mount Wutai, and Wang's Courtyard exhibit high EffSize and Efficiency values alongside low Constraints values. This highlights their elevated levels of structural holes, granting them competitive advantages within the network. In contrast, nodes like Yellow River Iron Bull, Fenglingdu, and Yan Xishan's Former Residence show opposite trends. These nodes are more constrained by others and occupy less advantageous positions in the structural hole network.

4.2.5 Cohesive subgroups

CONCOR is commonly used to identify groups with similar characteristics within a network in SNA (Riswanto et al., 2023). We used CONCOR to analyse a cohesive subgroup of the tourist flow network in Shanxi (Gan et al., 2021). By identifying tourism zones through cohesive subgroups, and revealing tourists' preferences for combining tourist attraction routes. Eight closely connected clusters were formed based on the degree of association between various tourist attractions, detailed in Table 2.

Table 2. **Classification of cohesive subgroups**

Num	Node name
1	Cao Family Courtyard, Five major museums, Donghu Vinegar Garden, Shanxi Bronze Museum, Fenhe Park, Taiyuan Old Town, Shanxi Geological Museum, Mengshan Scenic, Shanxi Provincial Museum, Twin Towers Park, Taiyuan Ancient County, Yuci Old Town, China Coal Museum, Jinci
2	Taihang Mountain Grand Canyon, Qianfo Temple, Mian Mountain, Qikou Ancient Town, Dazhai, Chang Family Manor, Qu Family Courtyard, Hukou Waterfall, Qiao Family Courtyard, Dayu Ancient Village, Pingyao Ancient City, Yao Temple, Wang Family Courtyard, Zhangbi Ancient Castle, Guangsheng Temple
3	Yan Xishan's Former Residence, Piantou Pass, Daizhou Ancient City, Laoniuwan Scenic, Luya Mountain Scenic, Xinzhou Ancient City, Chongfu Temple, Niangzi Pass
4	Mount Wutai, Earth Forest, Datong Ancient City, Datong Volcanoes Geopark, Hengshan Scenic, Datong Museum, Yingxian Wooden Pagoda, Yungang Grottoes, Hunyuan County, Yanmen Pass
5	Puji Temple, Dongyue Temple, Guanque Tower, Fenglingdu, Yongle Palace, Changping Guandi Temple, Salt Lake Scenic Area, Haizhou Guandi Temple, Mausoleum of Emperor Shun, Yellow River Iron Bull
6	Guangrenwang Temple, Dahuaishu, Li Family Courtyard, Yunqiu Mountain
7	Guoyu Ancient City, Tianguan Palace, Xiangyu Castle, Guanyin Hall, Juemountain, Wangmangling, Lu'an City God Temple, Jade Emperor Temple
8	Wuxiang Red Tourism Education Base, Susan Cultural Park, Youyu Ancient Great Wall, Huangchengxiangfu, Jingdi Village

Source: Authors

Table 3 analyses the network density among cohesive subgroups within Shanxi's tourist flow. Regarding internal connections, Subgroup 4 exhibits the highest cohesion, with a density value of 0.7, significantly higher than the other subgroups. Subgroups 5 and 2 follow. In contrast, Subgroup 8 shows weak internal cohesion, with a density of only 0.05.

Table 3. **Density matrix of cohesive subgroups**

	1	2	3	4	5	6	7	8
1	0.227	0.144	0.028	0.042	0.017	0.125	0.019	0.183
2	0.161	0.443	0.067	0.2	0.013	0.017	0.015	0.04
3	0.056	0.081	0.139	0.211	0	0.028	0	0
4	0.1	0.227	0.178	0.7	0.01	0	0	0.02
5	0.042	0.007	0	0.02	0.5	0.25	0.022	0.08
6	0.146	0.033	0.028	0.025	0.175	0.167	0.028	0.2
7	0.019	0.015	0	0.033	0.033	0.028	0.292	0.222
8	0.067	0.053	0.022	0.02	0.04	0.15	0.289	0.05

Source: Authors

For interconnections among subgroups, Subgroups 1, 2, 6, and 8 demonstrate radiative effects on all other subgroups. Subgroup 1 has the strongest radiative effect on Subgroup 8 and the weakest connection with Subgroup 5. Similarly, Subgroup 2 exhibits the highest radiative effect on Subgroup 4 and the lowest on Subgroup 5. Subgroup 3 maintains its strongest connection with Subgroup 4, surpassing its internal cohesion, but its connections with Subgroups 5, 7, and 8 remain limited, especially as there are no connections with Subgroups 5 and 7.

In summary, Subgroups 2, 4, and 5 show stronger internal connections, whereas other subgroups and interconnections between them are relatively sparse. This fragmentation highlights a disjointed and individualistic tourism landscape, particularly with Subgroup 5, centred around Yuncheng, which maintains minimal connections to other subgroups and operates independently from the broader network. Strengthening cooperation and communication among these subgroups is urgently needed.

4.3 The application of Pole-Axis Theory in tourist flow network structures

4.3.1 The criteria and results for defining poles

(1) The criteria for defining poles

A pole is the core of the tourism spatial structure, consisting of key nodes that significantly influence regional development (Wang et al., 2024). The identification of nodes in the tourist flow network in this study is based on the inherent properties of network structure, utilizing centrality and structural holes as measurement criteria. A combination of centrality and structural hole values influences the role and position of tourism nodes in the overall network. Generally, the higher the centrality of a single node, the stronger its ability to attract other nodes and act as a mediator, while facing fewer constraints from different nodes (Cui & Li, 2020). Based on this idea, the tourist flow node comprehensive value is built, as shown in Formula 1.

$$Value = OutD + InD + InC + OutC + Bet + Effsize + Efficie - Cons \qquad (1)$$

After normalizing the relevant indicators of centrality and structural holes, the comprehensive value of each node in Shanxi Province is measured according to Formula 1. The results are categorized into core nodes, key tourism nodes, and general tourism nodes (Table 4).

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Issue 32, volume 17, ISSN 1804-5650 (Online)
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Table 4. **Centrality, Structural hole Measurement Results, and Role Placement in Tourist flow Networks in Shanxi Province**

	Centrality					Structural hole				
Nodes	OutDeg	InDeg	inClos	outClos	Between	EffSize	Efficie	Constra	value	Role
Pingyao Ancient City	25	34	63.478	35.437	726.99	27.271	0.758	0.116	6.516	core node
Jinci	26	26	53.676	36.139	564.61	23.74	0.742	0.133	5.793	core node
Mount Wutai	22	19	52.518	34.434	425.19	18.183	0.699	0.158	4.809	key node
Wang Family Courtyard	21	20	53.285	35.266	370.44	18.427	0.709	0.16	4.802	general nodes
Hukou Waterfall	19	18	52.899	35.266	398.71	19.5	0.722	0.151	4.770	general nodes
Taiyuan Old Town	20	18	47.712	34.272	270.73	17.316	0.693	0.167	4.346	general nodes
Yingxian Wooden Pagoda	18	13	50	33.182	257.39	14.935	0.649	0.178	4.251	general nodes
Shanxi Provincial Museum	17	20	53.285	33.486	235.52	15.905	0.663	0.173	4.176	general nodes
Haizhou Guandi Temple	8	8	41.714	29.317	99.797	8.438	0.703	0.304	4.020	key node
Taihang Mountain Grand Canyon	9	14	49.324	31.878	415.50	15.522	0.817	0.183	3.977	general nodes
Yanmen Pass	18	18	52.518	33.796	298.30	15.556	0.676	0.175	3.905	general nodes
Qikou Ancient Town	15	11	48.026	32.883	205.61	14.192	0.71	0.196	3.643	general nodes
Datong Ancient City	16	16	49.66	32.589	192.63	11.547	0.608	0.2	3.563	general nodes
Yungang Grottoes	13	17	52.518	31.466	226.45	12.083	0.636	0.212	3.549	general nodes
Qiao Family Courtyard	14	14	48.026	33.486	174.02	13.232	0.63	0.197	3.522	general nodes
Hengshan Scenic	13	18	50.694	32.159	161.29	11.484	0.574	0.203	3.394	general nodes
Taiyuan Ancient County	12	5	40.782	31.878	21.752	7.971	0.531	0.266	3.383	general nodes
Xinzhou Ancient City	10	8	43.195	30.165	43.285	10.806	0.675	0.241	3.328	key node
Luya Mountain Scenic	10	9	44.785	31.878	73.292	9.921	0.62	0.245	3.197	general nodes
Donghu Vinegar Garden	8	8	45.062	31.197	30.191	5.75	0.479	0.337	2.989	general nodes
Mean	8.014	8.014	41.1	29.49	105.45		0			

Source: Authors

(2) The results for poles

Core nodes are critical to Shanxi Province's tourism development, serving as the vanguards of the province's overall growth. Pingyao Ancient City and Jin Ci stand out with significantly higher comprehensive scores than other nodes. Pingyao Ancient City occupies a dominant position in the network, demonstrating unmatched authority and exceptional aggregation and diffusion capabilities, thus earning its designation as a core node.

The identification of key nodes is typically based on administrative divisions, selecting the core attractions of each city as key destinations to support the dispersal of visitors from core scenic areas and drive local tourism development. However, the CONCOR in this study reveals that while tourism destinations still exhibit a degree of geographical proximity, some have transcended administrative boundaries. Therefore, this study defines key nodes based on the core attractions of the eight closely connected tourism clusters formed by tourists' autonomous choices.

The two core nodes function as transportation hubs, attracting a large influx of external tourists and subsequently distributing them to the core attractions of the eight tourism clusters. These core attractions further allocate tourists within their respective clusters to other destinations. Therefore, the core attractions of the eight clusters are defined as key nodes, primarily serving to drive the development of each cluster. Since the two core nodes are already the core attractions of the first and second clusters, no additional key nodes are designated for these two clusters. Based on the comprehensive value and cohesive subgroup analysis, the identified key nodes are Xinzhou Ancient City, Wutai Mountain, Guandi Temple in Jiezhou, Li Family Courtyard, Tianguan Palace, and Huangcheng Xiangfu.

The remaining nodes are categorized as general tourism nodes, forming the foundational structure of the network. This hierarchical framework establishes a gradient development model, core–key–general, where core nodes extend.

4.3.2 The results for axis

The axis is an infrastructure corridor connecting multiple poles. It functions as a socio-economic agglomeration belt, playing a crucial role in the diffusion and linkage of poles (Wang et al., 2024). Applying this theory to tourism destinations, the axis in the "pole-axis" system can be understood as a key corridor connecting poles with strong comprehensive capacity and significant development potential. Building on this perspective, the present study integrates Shanxi's major tourism nodes with its transportation network to delineate three principal tourism development axes.

As shown in Graph 6, the poles in Shanxi Province are primarily distributed along major transportation routes. Based on the hierarchy of poles and the province's transportation conditions (Song et al., 2025), this study proposes establishing the first tourism development axis along the Datong-Xi'an high-speed railway and the Jincheng-Taiyuan intercity railway. This forms a "人"-shaped tourism development corridor, leveraging the radiation effects of core nodes and sub-core nodes to drive the tourism development of general nodes. This tourism development axis is the most critical in the province, connecting most tourism poles across Shanxi.

Additionally, the "十-shaped" transportation network formed by the Da-Yun, Qing-Yin, and Jing-Kun expressways serves as the second tourism development axis, complementing the first axis. Centred on the Taiyuan-Jinzhong cluster, it promotes tourism development in the Lüliang and Yangquan clusters. In the future, the three ongoing tourism highways along the Yellow River, Great Wall, and Tai hang Mountains could be considered as the third tourism development axis. Ultimately, this would form a "困"-shaped three-tiered tourism development corridor across Shanxi Province, optimizing the spatial structure of tourism and enhancing regional tourism coordination and development.

4.3.3 The zone formed based on the pole-axis

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Issue 32, volume 17, ISSN 1804-5650 (Online)
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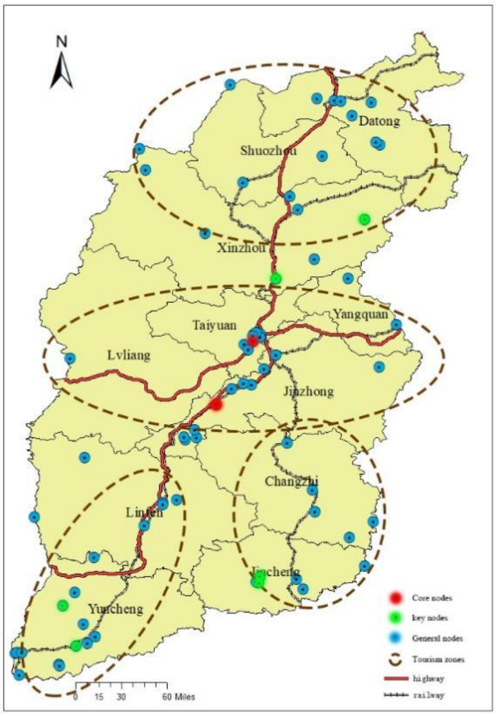
In the pole-axis theory, forming a "zone" mainly relies on the core nodes' driving effect and the axis's extension effect. As poles and axes continue to develop and concentrate, geographically proximate nodes strengthen their division of labour and cooperation under the influence of the axis, gradually forming a relatively complete and independent zone (Lu, 2024; Karácsony et al. 2024). In conventional research, delineating zones often relies on scholars' expertise (Song et al., 2025). In contrast, the CONCOR in SNA is based on the interconnections between nodes (Riswanto et al., 2023), forming closely linked clusters or zones. This approach minimizes the influence of subjective biases, ensuring more objective research outcomes.

Based on CONCOR (see supplementary material 2), the eight clusters were formed into four primary zones (Graph 6): Central Shanxi Zone: Taiyuan, Jinzhong, Yangquan, and Lvliang. Northern Shanxi Zone: Datong, Xinzhou, and Shuozhou. Southwestern Shanxi Zone: Yuncheng and Linfen. Southeastern Shanxi Zone: Changzhi and Jincheng. The result provides a basis for the delineation of "zones" within the pole-axis theory framework.

Graph 6. **Shanxi Province tourism spatial structure system.**



Source: Authors

5. Discussion

5.1 Theoretical implications

The pole-axis theory is a crucial analytical framework for regional development, particularly in the tourism sector, as it integrates cities, transportation, and resources into a closely interconnected spatial structure (Lu, 2024). This study advances the theory in two respects. First, it introduces SNA into the pole–axis framework, shifting the scale of analysis from traditional provincial or municipal levels to the finer scale of tourism destinations (Wang et al., 2023; Wang et al., 2024). This yields a "dual-core–eight-cluster–four-zone" spatial structure, offering a more detailed and behaviourally grounded perspective on destination development. Second, the study establishes explicit correspondences between network indicators and elements of the pole–axis framework. Traditionally, the identification of "poles" relied heavily on quantitative methods, such as composite indices, TOPSIS. while the delineation of "axes" and tourism "zones" often depended on expert judgment (Song et al., 2025). Here, the "comprehensive value of tourist flow nodes" (calculated from centrality and structural hole metrics) is employed to identify poles (Cui & Li, 2020), while tourism zones are delineated through cohesive subgroups, providing a quantitative and objective alternative. Axes are defined by integrating pole distribution with Shanxi's existing and planned transportation systems.

In the pole–axis theory, axes are conventionally defined as infrastructure corridors that connect multiple poles, typically aligned with transportation systems and differentiated by hierarchical levels (Wang et al., 2024). For this reason, the eight clusters identified in the CONCOR were not directly designated as axes. Instead, they represent sets of closely connected tourist attractions that can be regarded as potential travel routes in this study (Riswanto et al., 2023). To designate them as axes, however, would require explicit integration with actual transportation infrastructure, which is complicated by the diverse combinations of road connections between attractions. Therefore, this study adheres to the conventional definition of axes established in previous research (Song et al., 2025). Nevertheless, the objective derivation of these clusters through cohesive subgroups demonstrates that behaviourally linked destinations could serve as a valuable quantitative basis for axis delineation when aligned with transport corridors (Lu, 2024). While not directly applied for axis delineation in this study, these clusters could be incorporated into the "人－十－口" system to build a transport and route network more closely aligned with visitor demand, thereby facilitating Shanxi's spatial transition from poles to axes and, ultimately, to zones.

5.2 Practical implications

The findings also provide implications for tourism planning and destination management. At the node level, high-centrality hubs such as Pingyao Ancient City and Jinci Temple function as gateways that should be leveraged for external promotion, visitor dispersal, and balanced growth across clusters (Guo & Liu, 2021). By contrast, peripheral sites such as Niangziguan and Changping Guandi Temple should strengthen intra-cluster linkages and rely on local key nodes to attract nearby visitors. The results also show that, despite the emergence of new attractions (e.g., Five major museums, Fenglingdu, Taiyuan Ancient County) impacting traditional hotspots, tourists retain a marked preference for high-grade traditional resources: the top 21 attractions by degree centrality are all rated 4A or 5A. This indicates that upgrading and branding high-level attractions remain essential, while new attractions should be integrated into existing routes to diversify visitor experiences.

At the cluster level, the study identifies eight tightly connected tourism clusters based on actual tourist flows, differing from the eleven clusters defined by the Shanxi government (CTDSX, 2022). This divergence suggests that geographic proximity and transport linkages shape tourists' route planning more strongly than administrative boundaries (Paulino et al., 2021). For example, the growing integration of Taiyuan and Jinzhong has led many visitors—and even travel agencies—to package their attractions as a single destination. Future development should thus focus on breaking administrative barriers, strengthening inter-cluster cooperation, and prioritizing growth around these eight functional clusters.

At the regional scale, the Shanxi government's proposed "Yellow River–Great Wall–Taihang" tourism zones broadly correspond to the three regions identified in this study—southwestern Shanxi, northern Shanxi, and southeastern Shanxi—based on patterns of tourist flow. However, these zones remain relatively underdeveloped. The calculated comprehensive values show that five of the top eight attractions are located in central Shanxi, highlighting the enduring core role of this region in the province's tourism landscape. Therefore, while promoting balanced development across the three zones, it is crucial to consolidate the central zone's radiating function, leveraging the "困-shaped" corridor network strategy to enhance interregional connectivity and coordinated growth. This would facilitate a structured spatial transition from poles to axes and ultimately to zones.

Although Shanxi serves as the empirical case, this study employs the pole–axis theory to reveal the spatial structure of tourism through tourist mobility patterns, thereby providing theoretical insights and practical implications for spatial restructuring and sustainable tourism planning. This supports the view that tourism pattern mining is a scientific and feasible approach (Liu et al., 2024), while the findings extend the application scenarios of spatial geography theory in the era of big data and generate insights of broader relevance for the governance of other tourism destinations.

6. Conclusion

This study aimed to mine tourist movement behaviour to reshape the spatial structure of tourism destinations in underdeveloped regions, and to integrate relevant theories, thereby providing theoretical insights and practical implications for spatial optimization and sustainable tourism development. Drawing upon the framework of pole-axis theory and utilizing online travelogues from Ctrip, we employed data mining and SNA to reconstruct the tourist flow network structure in Shanxi Province. The findings demonstrate that tourist movement behaviour has significantly influenced the spatial configuration of tourism in Shanxi. In particular, the tourism spatial structure derived from tourist mobility patterns diverges from the government-designated spatial structure, underscoring a clear misalignment between official planning and actual tourist behaviour.

By integrating SNA with pole-axis theory, this study not only enriches methodological approaches in tourism geography but also offers a practical framework for optimizing spatial layout and enhancing destination competitiveness. The findings suggest that tourism planning should shift from a static, resource-based logic to a more dynamic, behaviour-driven perspective. Future strategies should prioritize flexible, demand-responsive spatial configurations that align with emerging travel patterns.

Future research can build on this study by further integrating SNA with pole–axis theory, particularly by linking tourist behaviour clusters with transportation infrastructure. This would not only deepen theoretical understanding of how tourist mobility reshapes spatial structures but also yield actionable insights for destination management. For instance, aligning organically formed clusters with planned transport corridors could guide investment in gateway hubs, optimize route design, and strengthen inter-destination connectivity. Moreover, applying this framework across diverse cultural and geographical contexts would help test its robustness and broaden its applicability, ultimately supporting more adaptive and sustainable destination development.

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