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RESEARCH

Beyond Mobility Volumes: Origin-City-Level Tourist Visitation Patterns Across Urban Attractions

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Abstract

Understanding tourist behavior at the origin-city level is essential for destination planning and regional tourism management. Most existing studies focus on aggregate intercity mobility volumes, overlooking how tourists from different cities distribute their visits across various attractions. This study addresses this gap by analyzing origin-city-level visitation patterns to three attraction categories (i.e., cultural-historic, natural scenery, and leisure) using weekly mobility data from over 300 Chinese cities to Nanjing during 2018–2019. First, the spatiotemporal heterogeneity of visitation to three attraction categories is analyzed. Second, a data-driven regionalization is conducted based on intercity similarities in attraction visitation. Logistic regression is then employed to examine how city-level characteristics, including socioeconomic, demographic, geographic, and functional attributes, are associated with these visitation patterns. Results reveal pronounced spatial heterogeneity and two dominant visitation regimes covering approximately 92% of cities: one favoring cultural-historic attractions in northern China and Guangdong, and another exhibiting more balanced visitation between cultural-historic and nature-scenery attractions in southern regions. Regression analyses highlight the importance of demographic composition, geographic orientation, urban functions, and digital attention in shaping intercity visitation differences. These findings provide empirical support for behavior-informed tourism planning, enabling policymakers to align destination management and resource allocation with the visitation patterns of different origin cities.

Keywords Origin-city-level mobility · Tourist visitation patterns · Multilayer network analysis · Data-driven clustering

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Introduction

Understanding tourist mobility requires not only knowing how many people travel between cities, but also how these intercity flows are translated into visitation patterns across different types of places within destinations. Such patterns reflect how tourists allocate their activities after arrival and provide insights into the functional role of cities as tourism destinations. Compared with generic forms of human mobility, tourist mobility explicitly links large-scale intercity movement with differentiated visits to urban attractions (Liu et al., 2022; Wang et al., 2024).

Existing studies on tourist mobility have largely emphasized aggregate intercity flows, focusing on volumes, distances, and spatial interaction intensity between origins and destinations (Cui et al., 2020; Park et al., 2022). While these studies have advanced our understanding of regional tourism systems, they provide limited information on how tourists from different origins distribute their visits across different categories of attractions after arriving at the same destination. In practice, tourists rarely experience a city as a homogeneous space; instead, they engage selectively with cultural-historic sites, natural scenery, and leisure-oriented facilities, which may be visited unevenly by tourists from different origins. Examining origin-city-level attraction visitation patterns therefore provides a necessary perspective for understanding internal heterogeneity within destinations and for revealing structured differences in tourism engagement that are not captured by aggregate flow-based analyses.

Two main research gaps motivate this study. First, although attraction-level tourism studies exist, most focus on individual behavior or specific attraction types, particularly cultural-historic or natural sites (Kim et al., 2007; Meng et al., 2024). Leisure-oriented activities, such as shopping, dining, and entertainment, remain underrepresented, despite their growing importance in contemporary tourism. Moreover, attraction visitation has rarely been examined systematically at the origin-city level, limiting comparative analysis of how tourists from different cities structure their visits within the same destination. Second, while regional differences in tourism flows are well documented, less is known about intercity similarities in attraction visitation structures and how such similarities evolve over time. Identifying groups of cities with similar visitation patterns can reveal higher-level regional structures and inform coordinated tourism planning.

At the same time, digital platforms increasingly mediate tourism behavior. Online search activities and other forms of digital human activity shape destination awareness, information acquisition, and trip planning (Figueredo et al., 2017). Although prior research has shown that digital platforms can influence tourism demand, their role in explaining differences in attraction visitation patterns across cities remains insufficiently explored. Based on these gaps, this study addresses the following research questions:

- RQ1: How do origin-city-level visitation patterns to different categories of urban attractions (cultural-historic, natural scenery, and leisure) vary across space and over time?
- RQ2: Which cities exhibit similar attraction visitation structures, and how are these similarities organized spatially and temporally?

- RQ3: Which city-level characteristics are associated with these visitation patterns?

To answer these questions, weekly tourist mobility data from over 300 Chinese cities traveling to Nanjing during 2018–2019 is analyzed. For each origin city and week, the proportional distribution of visits across attraction categories is calculated, capturing visitation structures beyond aggregate flow volumes (RQ1). A multilayer similarity network is then constructed, in which each layer represents a week and intercity links reflect similarities in visitation distributions. Community detection identifies groups of cities with similar visitation structures and their temporal evolution (RQ2). Finally, logistic regression is used to examine how socioeconomic, demographic, geographic, and functional attributes, including online search activity, are associated with these city clusters (RQ3).

Literature Review

Intracity and Intercity Tourist Mobility

Research on tourist mobility generally falls into two strands: intracity mobility and intercity mobility. Intracity studies focus on movements within destinations and their implications for transportation systems, spatial organization, and crowd management. Empirical evidence shows that intracity tourist flows often follow distance decay patterns and are shaped by urban morphology and accessibility (Jin et al., 2018; Mohammadpour & Mehrjou, 2023). Network-based analyses further suggest that tourists and residents exhibit distinct mobility structures, with tourist movements typically more centralized and attraction-oriented (Wang et al., 2021).

Intercity tourism research, by contrast, has largely concentrated on aggregate flows between origins and destinations. Spatial interaction models and OD flow analyses have been widely used to examine how distance, transport infrastructure, and socioeconomic factors shape tourism flows (Wang et al., 2024; Yang et al., 2019). Network approaches reveal structural differences across travel purposes and highlight the heterogeneous roles of cities within tourism systems (Cui et al., 2020; Wen et al., 2025). However, these studies typically treat destinations as undifferentiated nodes, providing limited insight into how tourists from different origin cities allocate their activities within destinations.

Attraction-Level Visitation and Origin-City Perspectives

A growing body of work has begun to explore attraction-level visitation, often emphasizing individual behavior. Some studies examine how tourists choose between cultural-historic and natural attractions under different temporal or contextual conditions (Kim et al., 2007; Meng et al., 2024), while others link attraction choices to demographic or socioeconomic characteristics (Zhang et al., 2013). Nevertheless, most of this research focuses on a narrow set of attraction types and rarely considers leisure-oriented activities, which have become increasingly central to urban tourism. Moreover, attraction visitation is seldom analyzed comparatively at the origin-city level, limiting understanding of regional similarities and differences in visitation structures.

Digital Technologies and Tourism Behavior

Digital technologies have further reshaped tourism behavior by influencing information search, destination image formation, and trip planning. Studies show that online platforms and social media can affect tourism demand and destination visibility (Wong et al., 2020; Zeng & Gerritsen, 2014), although their impacts are context-dependent (Tham et al., 2020). Existing research has primarily examined whether digital activity increases tourist numbers, while relatively little attention has been paid to how it relates to the composition of attraction visitation within destinations.

Network-Based and Multilayer Approaches in Tourism Research

Methodologically, complex network analysis has been widely applied to tourism and mobility research (Wang et al., 2021; Xu et al., 2023). Multilayer networks, in particular, provide a flexible framework for representing temporal dynamics or multiple types of relationships (Jia et al., 2022; Pastor-Satorras et al., 2015). By modeling each time step as a layer and linking cities across layers, multilayer networks enable the identification of evolving similarity structures that cannot be captured by independent, static clustering approaches (Kivelä et al., 2014). In this study, a multilayer similarity network is employed to examine how origin cities align in terms of attraction visitation structures over time.

Research Contributions

This study contributes to the literature in three ways. First, it advances tourism mobility research by shifting attention from intercity volumes to origin-city-level attraction visitation structures across multiple attraction categories. Second, it introduces a multilayer network framework to identify spatiotemporal clusters of cities with similar attraction visitation structures. By explicitly linking cities across consecutive time layers, this approach preserves temporal continuity and ensures the comparability of city groupings over time, offering a coherent and data-driven perspective on regional tourism organization. Third, it examines how a range of city-level characteristics are associated with observed visitation patterns.

Study Area and Datasets

Study Area

This study focuses on intercity tourist mobility from over 300 cities across mainland China to Nanjing, an important hub located in the eastern inland region of the country. As the former capital of multiple dynasties and a major node in the Yangtze River Delta, Nanjing plays a significant role in attracting diverse types of domestic tourists. Figure 1 presents the log-transformed total number of tourists from each city over two years. A clear spatial pattern is observed: the highest tourist volumes originate from Nanjing itself and neighboring cities, with demand gradually declining as

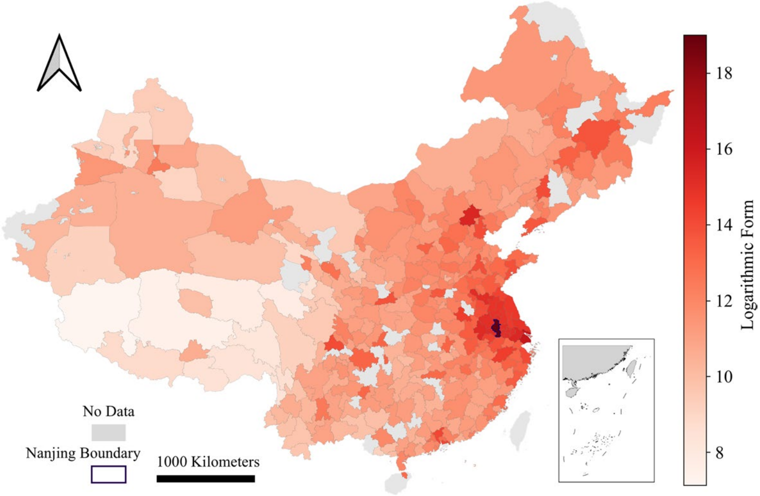

Fig. 1 The log-transformed total number of tourists to Nanjing from more than 300 cities in China over two years

the distance from Nanjing increases, particularly toward inland and western regions. While this spatial distribution reflects an intuitive pattern shaped by proximity and accessibility, it only captures the surface-level dynamics of intercity tourist flows. It is important to move beyond aggregate tourist volumes and examine patterns of visitation to different attractions, which refers to how tourists from different origin cities are distributed across various types of attractions. Uncovering these latent structures offers a more refined and detailed understanding of tourism industry and supports more targeted destination planning.

Datasets

This study integrates six types of datasets to explore tourists' visitation patterns to different attractions within destination at origin-city level, and its potential influencing factors from multidimensions, as shown in Table 1. The core tourist dataset, obtained from the Nanjing Tourist Big Data Monitoring Platform, records the weekly number of tourists from over 300 cities in mainland China to Nanjing's major attractions during 2018 and 2019. Attractions are grouped into three categories: Cultural History (e.g., Presidential Palace, Huiji Temple), Natural Scenery (e.g., Xuanwu Lake, Qixia Mountain), and Leisure (e.g., Ginkgo Lake Resort, Hongshan Zoo).

To characterize city-level socioeconomic conditions, the census data from the National Bureau of Statistics (2020) is incorporated, including indicators such as population size, per capita gross domestic product (GDP), urbanization level, and demographic structure. The Points of Interest (POI) dataset from Amap (2018) captures the functional composition of cities across multiple categories, including shopping, dining, accommodation, transportation, tourist facilities, daily services, entertainment, and infrastructure. These indicators reflect the diversity and specialization of urban

Table 1 Description of multi-source data used in the study

Data Type	Description	Period	Source
Tourist Mobility	Weekly tourist counts by attraction type	2018–2019 (weekly)	Nanjing Tourist Monitoring Platform
Census	Population, GDP, demographics	2020	National Bureau of Statistics
POI	Urban function indicators	2018	Amap
Administrative Boundaries	City-level polygon shapefiles	2018	Administrative division
Baidu Search Index	Daily search volume for Nanjing and its attractions	2018–2019 (daily)	Baidu Index
Migration Willingness index	Navigation-based mobility intent indicator	2018.06–2019.12.06.12 (daily)	Amap Migration

functions. Administrative boundary data provides spatial framework for computing geographic metrics such as distance and azimuth from each city to Nanjing.

Additionally, two human behavioral datasets in digital space are included. The Baidu Search Index reflects digital attention toward Nanjing and its attractions at the city level, with daily resolution from 2018 to 2019. The Amap-based Migration Willingness Index approximates intercity travel intention by tracking navigation-based search behaviors, serving as an indirect proxy for real-world mobility desire at origin-city level. While the calculation method for this index is not publicly disclosed, higher values suggest stronger intent to visit Nanjing.

Methodology

This study employs a four-stage analytical framework (Fig. 2) to investigate visitation patterns to different attraction categories within a destination. First, city-level attraction visitation profiles are constructed by calculating the proportions of visits to three attraction categories (i.e., cultural-historic, natural scenic, and leisure places) on a weekly basis. These proportions characterize how visitors associated with each origin city distribute their visits across different attraction categories over time, forming a temporal sequence of visitation patterns for each city. Second, based on these weekly visitation profiles, a multilayer similarity network is constructed to capture intercity similarities in attraction visitation patterns over time. Each layer of the network corresponds to one week, and nodes represent cities, with edge weights reflecting the similarity of their attraction visitation distributions in that week. Network-level metrics, such as node degree and average shortest path length, are used to examine the temporal evolution of the overall similarity structure.

Third, community detection is applied to multilayer similarity network to identify groups of cities exhibiting similar attraction visitation patterns. This process

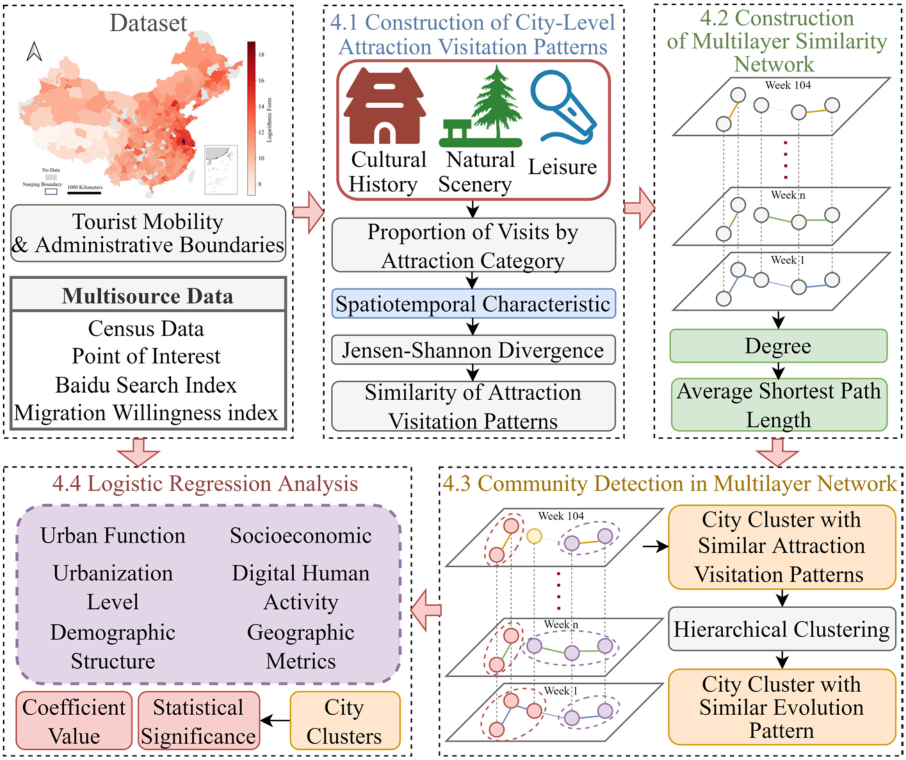

Fig. 2 Analytical framework of the study

yields a time series of community memberships for each city, reflecting the temporal evolution of its visitation behavior. To systematically summarize these temporal dynamics and identify stable visitation regimes, hierarchical agglomerative clustering to the sequence of weekly community labels for each city is further applied. This step groups cities according to the similarity of their entire temporal trajectories, producing a single, time-invariant cluster label that encapsulates each city's dominant attraction visitation pattern and its temporal stability. Finally, logistic regression analysis is conducted using these agglomerative clustering-derived labels as the dependent variable. Because these labels are fixed over time yet derived from temporal community dynamics, they provide a temporally informed but cross-sectional representation of visitation behavior. City-level attributes, including socioeconomic conditions, demographic structure, geographic location, urban development characteristics, and digital engagement indicators, are then used as explanatory variables to examine the factors associated with different dominant attraction visitation patterns. This design ensures consistency in temporal granularity between dependent and independent variables while preserving the influence of temporal evolution in the outcome of interest. The detailed methodology for each stage is presented in the following subsections.

Construction of City-Level Attraction Visitation Patterns

In this study, visitation patterns to different attractions are examined from two dimensions: the proportion of visits to specific attraction categories and the similarity of these visitation patterns between origin cities. To address RQ1, the proportion of visits to each attraction category, cultural-historic (CH), natural scenery (NS), and leisure (LE), is calculated relative to the total number of attraction visits from each origin city in a given week, as shown in Eq. (1). This proportion allows for standardized comparisons across cities with different population sizes or travel volumes.

$$Ratio_c^i\left(\mathrm{t}\right) = \frac{V_c^i\left(t\right)}{V_c^{total}\left(t\right)} \tag{1}$$

Where $Ratio_c^i\left(\mathrm{t}\right)$ is the ratio of visits to category i (i.e., CH, NS, or LE) from city c at time t; $V_c^i\left(t\right)$ denotes the number of visits to category i; and $V_c^{total}\left(t\right)$ is the total number of visits from city c at time t.

Beyond analyzing the spatiotemporal variation in the proportion of visits to each attraction category, the study also evaluates the similarity in attraction visitation patterns between origin cities. To quantify this similarity, the Jensen-Shannon (JS) divergence is applied to measure the difference between two cities' category-based visit proportions, as shown in Eq. (2). Since the JS divergence ranges from 0 (indicating identical distributions) to 1 (indicating completely different distributions), the similarity between two cities is defined as one minus the JS divergence, as shown in Eq. (3). This similarity index forms the basis for constructing the multilayer similarity network used in the subsequent clustering analysis.

$$JS\left(P||Q\right) = \frac{1}{2}D_{KL}\left(P||M\right) + \frac{1}{2}D_{KL}\left(Q||M\right), whereM = \frac{1}{2}(P+Q) \tag{2}$$

$$S_{cc'} = 1 - JS\left(P||Q\right) \tag{3}$$

For two cities c and c',P and Q represent the visit proportion distributions across all attraction categories for each origin city. The Kullback-Leibler divergence D_{KL} quantifies the difference between these two distributions. The similarity score $S_{cc'}$ measures the degree of similarity in attraction visitation patterns between the two cities, where a higher value indicates that the distribution of tourists across attractions is more alike.

Construction of the Multilayer Similarity Network and Relevant Metrics

To capture the spatiotemporal evolution of intercity similarities in attraction visitation patterns, a multilayer similarity network is constructed. The construction process consists of the following steps.

(1) Construct weekly attraction visitation distributions: for each origin city and each week, the proportional distribution of visits across three attraction categories

(i.e., cultural-historic, natural scenery, and leisure) is calculated. This results in a city-by-attraction distribution vector for each week, which serves as the basic representation of origin-city-level visitation structure.

(2) Measure intercity similarity within each week: for each week t, pairwise similarities between all cities based on their attraction visitation distributions using Jensen-Shannon similarity is computed. This measure captures how similarly two cities distribute their visits across attraction categories, independent of total visitor volume.

(3) Construct intra-layer similarity networks: each week is represented as a network layer $G^t = (V, E^t)$, where nodes V represent cities and edges reflect strong intercity similarities in that week. An undirected, weighted edge is formed between city c and c' if their similarity $S^t_{cc'}$ exceeds the 75th percentile of all similarity scores in week t. The choice of the 75th percentile was further validated through robustness checks: using alternative thresholds of the 60th and 80th percentiles, the community assignments remained highly consistent, with 96.4% of cities retaining the same weekly community at the 60th percentile and 94.8% at the 80th percentile. These results confirm that the 75th percentile captures strong intercity similarity and computation efficiency while maintaining stable and coherent network structures across weeks. The edge weight is defined as $S^t_{cc'}$, ensuring that each layer highlights the strongest similarity relationship while maintaining comparability across time.

(4) Link cities across time layers to form a multilayer network: all layers share the same set of nodes, corresponding to a consistent set of cities. To preserve temporal continuity, each city is connected to itself across adjacent weeks via interlayer edges. These interlayer connections ensure that community detection accounts not only for similarity within each week but also for the persistence and evolution of visitation patterns over time. The resulting multilayer network is defined as $G = (V, E, L)$, where $L = \{1,2, ..., T\}$ denotes the set of weekly layers spanning 2018–2019.

To illustrate the construction, consider a simplified example with ten cities observed over two consecutive weeks. In each week, a similarity network is built by connecting cities with highly similar attraction visitation distributions. If City A and City B exhibit similar visitation pattern in Week 1, they are connected by an intra-layer edge in Layer 1. In Layer 2, City A may become more similar to City C, forming a different set of intra-layer connections. Interlayer edges then connect City A in Week 1 to itself in Week 2, allowing the network to capture both changes in similarity relationships and the temporal continuity of each city's visitation behavior.

(5) Network-level metrics: following network construction, two metrics are calculated for each weekly layer to characterize overall network structure (Eqs. (4–5)): the average weighted degree and the average weighted shortest path length.

$$\bar{k}^t = \frac{1}{|V|} \sum_{i \in V} \sum_{j \in V} w^t_{ij} \tag{4}$$

$$L^t = \frac{1}{|V|\left(|V|-1\right)}\sum_{i\neq j} d_{ij}^t \tag{5}$$

Here $\overset{\_t}{k}$ denotes the average weighted degree of all nodes (i.e., cities) in the network at time t, where w_{ij}^t is the similarity-based edge weight between city i and city j. A higher value indicates stronger overall similarity among cities in that week. L^t represents the average weighted shortest path length, where d_{ij}^t is computed using the inverse of edge weights to reflect effective distance in the similarity network. Lower values of L^t indicate closer interconnectivity and more homogeneous visitation structures among cities.

Community Detection in Multilayer Similarity Network

To detect communities in the multilayer similarity network, the Infomap algorithm is applied. Infomap is an information-theoretic method that identifies network communities by minimizing the expected description length of a random walk trajectory on the network (Blöcker et al., 2022), as formalized in Eq. (6):

$$L\left(M\right) = q_{\curvearrowright} H\left(\varrho\right) + \sum_{i=1}^{m} p_i H\left(P_i\right) \tag{6}$$

Where $L\left(M\right)$ is the average description length per step, $q_{\curvearrowright}$ is the probability of exiting a module, $H\left(\varrho\right)$ is the entropy of the module-level codebook, p_i is the probability of staying within module i, and $H\left(P_i\right)$ is the entropy of the within-module codebook. The algorithm optimally compresses the trajectory of a random walker, thereby revealing communities as regions of dense intra-connections with sparse interconnections.

In temporal multilayer networks, Infomap treats each combination of a city and a specific time slice as a unique node. This means that the same city at different time points is represented by different node-layer pairs. Infomap allows flexible connections not only within each layer but also between layers, by linking the same city's nodes across adjacent time slices through interlayer edges. This approach enables Infomap to detect both stable and changing patterns in city clusters based on their weekly attraction visitation patterns. Each city is assigned a community label for every week, reflecting its position in the evolving network and allowing its behavior to be tracked over time.

To further group cities with similar long-term changes in community membership, an aggregate clustering is conducted. For each city, a vector of 104 values is created, representing its weekly community labels across the two-year period. Based on these vectors, hierarchical agglomerative clustering with Ward's method is applied (Waskom, 2021). This method minimizes differences within each group and identifies clusters of cities that have similar temporal changes in their attraction visitation patterns.

Logistic Regression Analysis

To examine the factors related to different attraction visitation patterns and their temporal evolution, logistic regression analysis is applied. This method is suitable for modeling a categorical outcome variable. The dependent variable is cluster label obtained from hierarchical agglomerative clustering of cities' temporal community labels. The independent variables include a range of city-level characteristics, such as socioeconomic conditions, demographic structure, geographic location, urban infrastructure, and indicators of digital human activity. These variables are collected from multiple sources to ensure broad coverage of urban features. To reduce multicollinearity and enhance the interpretability of the results, variables with a Variance Inflation Factor (VIF) greater than 10 or a Pearson correlation coefficient above 0.7 are removed. The final set of variables used in the model is presented in Table 2.

The refined dataset is then divided into training (70%) and testing (30%) subsets using stratified sampling to preserve the proportional distribution of clusters. The logistic regression model estimates the probability that a city i belongs to a particular cluster c, conditional on its feature vector X_i, using Eq. (7).

$$P\left(y_i = c|X_i\right) = \frac{e^{\beta_c^T X_i}}{\sum_{j=1}^{C} e^{\beta_j^T X_i}} \tag{7}$$

Table 2 Description and classification of independent variables used in logistic regression

Variable	Description	Category	Variable Type
Population	The total permanent population of the city	Socioeconomic	Numerical
Per capita GDP	Gross Domestic Product per capita	Socioeconomic	Numerical
POI type entropy	The entropy of point-of-interest types, measuring the diversity of urban functions	Urban Function	Numerical
POI type density (shopping, dining, hotel, tourist facilities, entertainment)	The proportion of each POI category relative to the total number of POIs in the city	Urban Function	Numerical
Azimuth	Directional azimuth from origin city to Nanjing, which is measured in degrees from the true north, increasing clockwise	Geographic	Numerical
Distance to Nanjing	The distance from origin city to Nanjing	Geographic	Numerical
Gender ratio	Ratio of male to female population	Demographic	Numerical
Age structure (0–14, 15–59)	The proportion of the population aged 0–14 and 15–59 relative to the total city population	Demographic	Numerical
Migration intent index	Navigation-based mobility intent index; higher values indicate stronger intercity mobility intention	Digital human activity	Numerical
Baidu search index	The proportion of Baidu searches related to 'Nanjing' and its attractions relative to the city's total 'Baidu' search volume	Digital human activity	Numerical
Rural population ratio	The proportion of rural residents relative to the total city population	Urbanization	Numerical

Where β_c is the coefficient vector associated with cluster c, and C is the total number of clusters. This multinomial logistic regression framework allows for modeling membership across multiple discrete categories. Model performance is evaluated using precision (the proportion of correctly identified positive cases among all predicted positives), recall (the proportion of actual positive cases correctly identified), F1-score (the harmonic mean of precision and recall), and Receiver Operating Characteristic curve (ROC curve), which illustrates the trade-off between the true positive rate and the false positive rate at various classification thresholds. The area under the ROC curve (AUC) is used as a summary measure, with higher AUC values indicating better overall model discrimination ability. Finally, regression coefficients and their statistical significance are examined to interpret the influence of each city-level attribute on the likelihood of cluster membership.

Results

Spatiotemporal Characteristics of Attraction Visitation Patterns

To address RQ1, the spatial and temporal distributions of attraction visitation patterns are analyzed for three categories: cultural-historical, natural scenery, and leisure attractions (Fig. 3). The spatial distribution is measured as the proportion of visitors from each origin city to each category, normalized by the total number of visits from that city across all three categories during the study period. The temporal distribution is calculated weekly by aggregating visits from all cities to each category and dividing by the total number of visits in that week.

The spatial results show clear regional differences. Cultural-historical attractions receive a higher share of visits from cities in northern China and Guangdong Province. Natural scenery is more frequently visited by cities in the southern regions. In contrast, leisure attractions show the highest proportions in Nanjing and its surrounding cities, extending toward the southwest. This distribution is consistent with established travel behavior patterns: leisure-oriented visits are often associated with short-distance, time-limited trips, while long-distance travelers are more likely to visit well-known cultural or natural places due to their perceived uniqueness and value. Local Moran's I analysis further highlights spatial autocorrelation patterns: for cultural-historical attractions, high-high clusters appear along the Inner Mongolia region and north of Nanjing, whereas low-low clusters are concentrated in cities near Nanjing; for natural scenery, high-high clusters are observed near Nanjing, with high-low clusters in northern and northwestern cities; for leisure attractions, low-low clusters occur north of Nanjing, and high-high clusters are concentrated in Nanjing and its nearby cities, indicating localized clustering of visitation behavior across regions.

Temporally, cultural-historical places consistently account for the largest share of weekly visits across the 104 weeks, followed by natural scenery, with leisure attractions receiving the lowest proportion, as shown in Fig. 3(g). A slight decline in the share of visits to cultural-historical places is observed from 2018 to 2019, with marginal increases in the shares of natural and leisure attractions. Analyzing weekly visi-

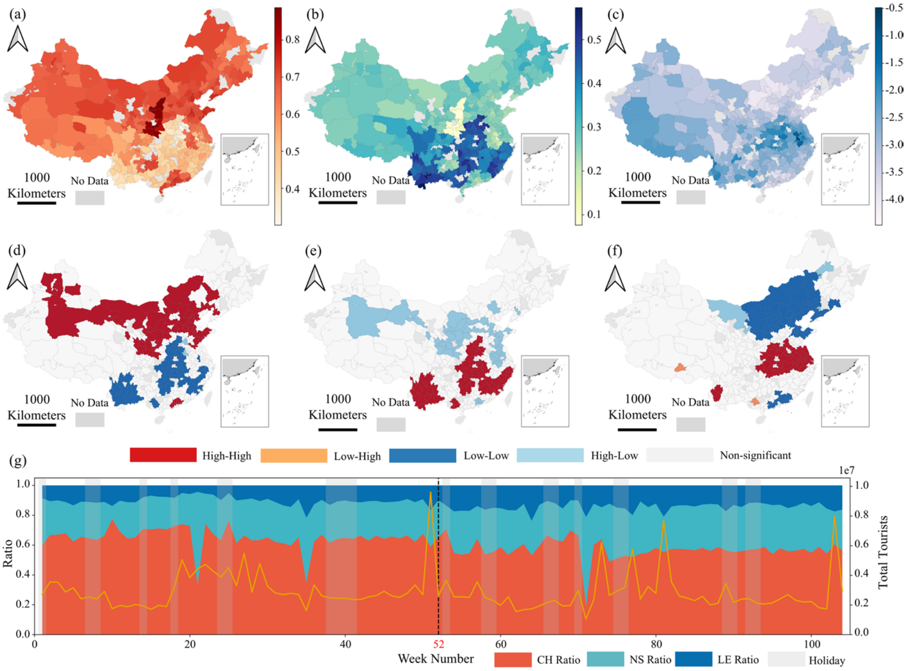

Fig. 3 Spatial and temporal patterns of tourist visitation across origin cities and attraction categories. (**a**-**c**) Spatial distribution of visitation ratios to three attraction categories across origin cities: Cultural History (CH) ratio (**a**), Natural Scenery (NS) ratio (**b**), and Leisure & Zoo (LE) ratio (**c**; log scale applied). Ratios are computed as the total visits in each category divided by the total visits to all categories over the study period (2018–2019). Cities with no available data are shown in grey. (**d**-**f**) Local Moran's I spatial autocorrelation for each attraction category (CH, NS, LE), indicating spatial clustering patterns of visitation ratios across cities. Light grey areas represent statistically non-significant Local Moran's I result ($p>0.05$). (**g**) Temporal evolution of visitation proportions and total tourist flows: the left axis shows the weekly proportion of visits to each attraction category aggregated over all cities, and the right axis (orange solid line) shows the weekly total number of tourists visiting Nanjing

tor counts reveals notable anomalies outside official holidays: peaks occur around late December (Christmas and year-end celebrations), as well as between week 20 (late May, corresponding to early summer) and week 30 (late July, likely driven by summer vacation travel), suggesting that seasonal and cultural factors can temporarily shift visitation patterns even outside statutory holidays. However, no clear structural changes are associated with national holiday periods, suggesting that short-term holiday effects do not significantly reshape the overall visitation patterns.

Temporal Dynamics and Community Structure Based on Intercity Similarity in Attraction Visitation Patterns

To further examine the structural characteristics and temporal evolution of attraction visitation patterns, a multilayer network community detection approach is applied, where each layer represents one week. Two key network metrics are calculated for each weekly layer: the average weighted degree and the average weighted shortest path length. As shown in Fig. 4(a), the average degree shows a clear decline in 2019 compared to 2018, indicating that cities became less similar in their attraction visitation patterns over time. The average shortest path length, smoothed to capture overall trends, remains more stable in 2019 than in 2018. This suggests that the network structure formed by cities with similar attraction visitation patterns experienced more fluctuations in 2018, whereas the connections among cities were more consistent and less volatile in 2019.

Community detection results reveal that the vast majority of cities consistently belonged to two dominant communities (i.e., Community 0 and Community 1). Community 0 includes approximately twice as many cities as Community 1. In each week, the proportion of cities not assigned to these two communities remains below 6%. As such, the analysis in this section focuses on these two main communities. Figure 4(b) presents violin plots showing the attraction visitation patterns across the two dominant communities. Community 0 is characterized by a higher proportion of visits to cultural-historical attractions, with relatively lower shares of natural scenery and leisure, the former being slightly more dominant than the latter. In contrast, Community 1 exhibits a more balanced distribution between cultural-historical and natural scenery visits, along with a notably higher proportion of leisure-related visitation, approximately twice that observed in Community 0. These differences represent distinct city-level visitation regimes and aggregate behavioral patterns across origin cities.

To explore whether cities exhibited temporal changes in their attraction visitation patterns, an aggregate clustering analysis is conducted based on the weekly community membership trajectories. Cities not belonging to Community 0 or Community

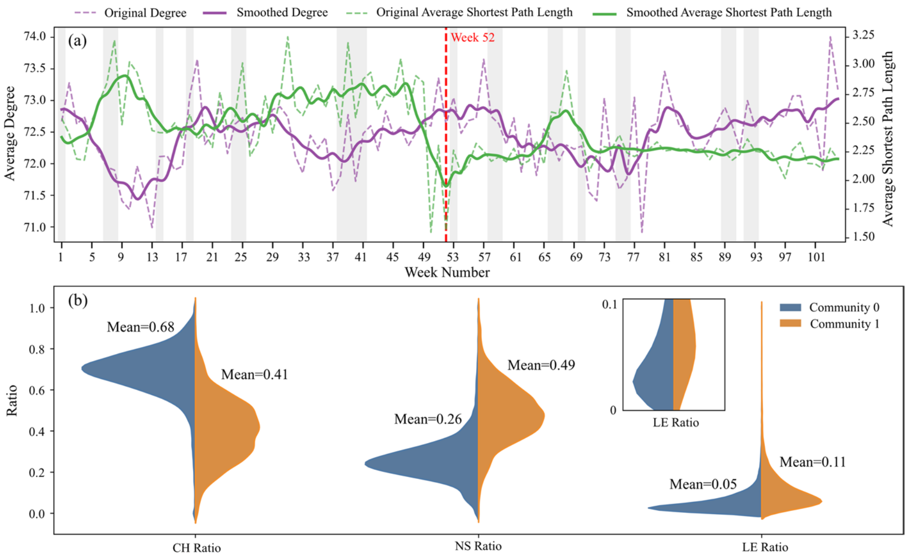

Fig. 4 (**a**) Temporal trends of average degree (purple) and average shortest path length (green) in multilayer similarity networks. Solid lines represent smoothed trends; dashed lines indicate original values. (**b**) Violin plots showing the distribution of cultural history ratio, natural scenery ratio, and leisure ratio for cities in Community 0 and Community 1

1 are grouped into a third intermediate category (Community 2) before clustering. The resulting aggregate clustering groups cities into six distinct evolution patterns, as shown in Fig. 5(a). Notably, approximately 92% of cities exhibited no change in community affiliation over time, indicating highly stable attraction visitation patterns. These stable cities are primarily clustered into two major groups: Cluster 0 and Cluster 1. The remaining four clusters represented cities with varying degrees of fluctuation in their attraction visitation patterns over time and different dominant community affiliations.

As shown in Fig. 5, Cluster 0 includes cities that are consistently assigned to Community 0 across time. Since Community 0 is characterized by a high proportion of visits to cultural-historic attractions and relatively lower shares for natural scenery and leisure, cities in Cluster 0 demonstrate a stable temporal pattern dominated by cultural-historic visitation. These cities are mainly located in northern China. Cluster 1 contains cities consistently belonging to Community 1, which shows a more

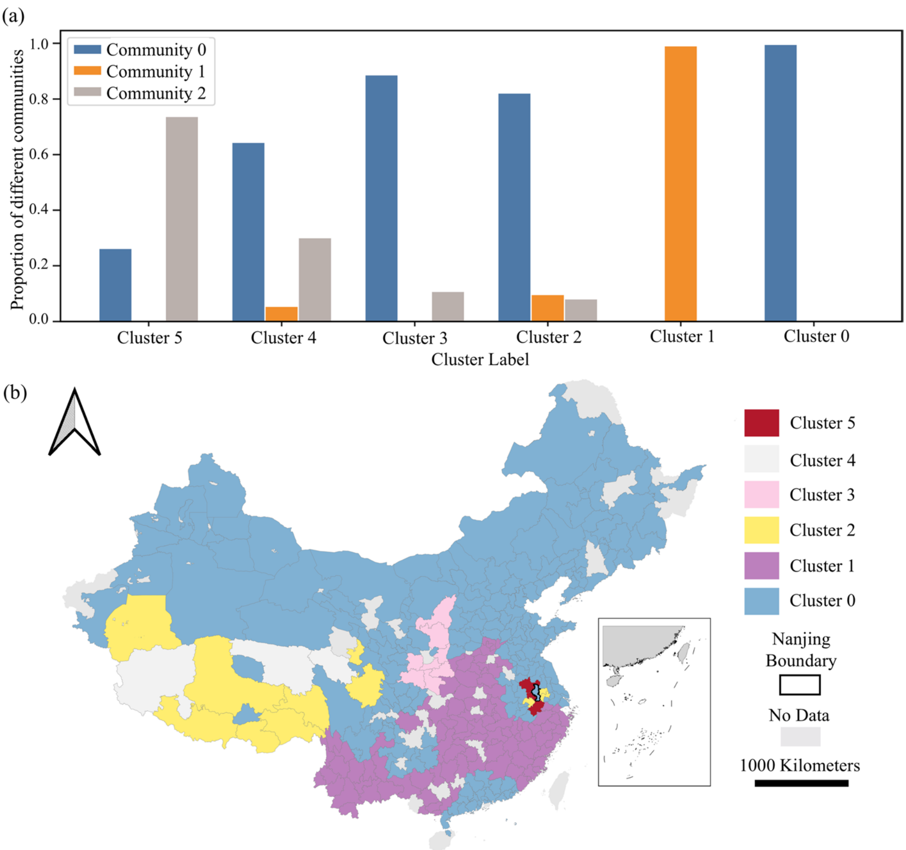

Fig. 5 (**a**) The proportions of original weekly community labels (0–2) within each agglomerative cluster, calculated across all cities and 104 weeks, summarizing the dominant community composition of each trajectory-based cluster. (**b**) Spatial distribution of the six identified clusters, representing groups of cities with similar temporal changes and attraction visitation patterns

balanced distribution between visits to cultural-historic and natural scenery attractions, along with a noticeably higher proportion of leisure-related visits. This cluster is mainly concentrated in southern China. The remaining four clusters include cities with less stable attraction visitation patterns over time. These cities are mostly located around Nanjing and in western regions such as Tibet, Shaanxi, and Qinghai. One possible reason is that these areas contribute fewer tourists to Nanjing, so their weekly visitation patterns are more affected by individual variation, resulting in higher temporal fluctuation.

Explaining Differences in Attraction Visitation Patterns Through City-Level Attributes

To examine the city-level factors influencing patterns of visitation to different attractions, a logistic regression analysis is conducted. The dependent variable is based on the aggregate clustering results from Sect. 5.2, focusing on Cluster 0 and Cluster 1, which together include approximately 92% of all cities. Most cities show stable attraction visitation patterns over time, meaning that their weekly community affiliations remain consistent. This highlights a high level of temporal stability in city-level attraction visitation behavior. Therefore, the analysis concentrates on understanding the differences between the two dominant groups: one group prefers cultural-historic attractions, and another group with a more balanced visits between cultural-historic and natural scenery categories.

The performance of the logistic regression model is shown in Fig. 6. The model exhibits strong discriminatory power, achieving an ROC AUC of 0.77, which indicates a good balance between sensitivity and specificity across classification thresholds. Moreover, the model attains a precision, recall, and F1-score of 0.68, suggesting it performs well in correctly identifying cities in each cluster while maintaining a balanced trade-off between false positives and false negatives.

Table 3 presents the logistic regression results linking city-level characteristics to differences in attraction visitation patterns. The dependent variable distinguishes between Cluster 0 with more visitations to cultural-historic attractions, and Cluster 1, where visits are more evenly distributed between cultural-historic and natural scenery places. The odds ratio (OR), calculated by taking the exponential of each regression coefficient, is used to interpret the results. An OR greater than 1 means

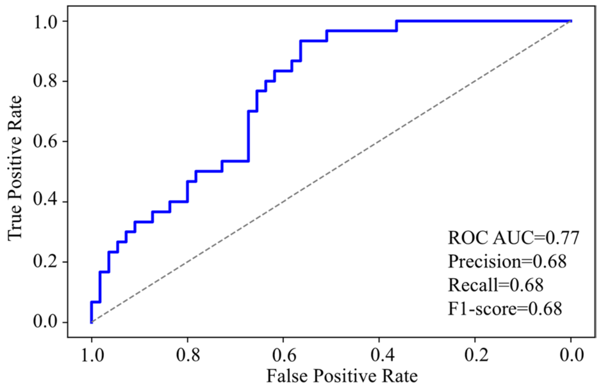

Fig. 6 Performance evaluation of the logistic regression model using ROC curve, precision, recall, and F1-score metrics

Table 3 The regression coefficients, OR, and their statistical significance of the logistic regression model

Variable	Coefficients	Odds Ratio	P_value
Population	−0.477	0.620	0.166
Per capita GDP	−12.094	0.000	0.006**
POI type entropy	0.171	1.187	0.298
Shopping density	0.321	1.379	0.425
Dining density	−1.166	0.312	0.002**
Hotel density	0.863	2.370	0.003**
Tourist Facility density	0.213	1.238	0.638
Entertainment density	−0.077	0.926	0.822
Azimuth	0.610	1.841	0.037*
Distance to Nanjing	−1.813	0.163	0.003**
Gender ratio	0.056	1.058	0.869
Age 0–14 ratio	1.224	3.400	0.002**
Age 15–59 ratio	1.346	3.841	0.009**
Migration intent index	−0.684	0.504	0.271
Baidu search index	−0.715	0.489	0.044*
Rural population ratio	−0.073	0.930	0.889

Note: * indicates the significant level at 0.05; ** indicates the significant level at 0.01

that higher values of the corresponding variable are linked to a greater likelihood of the city being in Cluster 1. Conversely, an OR less than 1 indicates higher values are associated with a greater likelihood of being in Cluster 0.

Among the statistically significant variables, per capita GDP has an extremely low OR (< 1), indicating that cultural visitation may be more appealing in economically advanced regions. Similarly, dining ratio, distance to Nanjing, and Baidu search index are all positively associated with Cluster 0, suggesting that cities with high dining density, far away from Nanjing, and stronger digital engagement are more inclined toward cultural-history-oriented visitation. Conversely, hotel ratio, azimuth, age 0–14 ratio, and age 15–59 ratio are positively associated with Cluster 1. These results suggest that cities with more tourist facilities, southeastern orientation relative to Nanjing, and larger proportions of younger and working-age populations tend to prefer a more balanced mix of cultural and natural attractions. In summary, the most influential factors differentiating tourist's visits include age structure, hotel and dining density, geographic indicators, and digital human activity, highlighting the joint impact of physical and digital space on attraction visitation patterns.

Discussion

This study advances the understanding of intercity tourist mobility by moving beyond aggregate flow volumes to examine origin-city-level visitation patterns across different types of urban attractions. Using weekly mobility data from more than 300 cities to Nanjing, we analyze how visitors are distributed across cultural-historic, natural, and leisure attractions, revealing patterns in origin-city tourism behavior. By integrating multilayer network analysis with multidimensional city-level indicators, this study provides a comprehensive perspective on regional differences in visitation patterns.

Spatial and Temporal Heterogeneity of Visitation Patterns (RQ1)

For RQ1, clear spatial heterogeneity in visitation patterns to different types of attractions is observed. Northern Chinese cities and Guangdong exhibit more visits to cultural-historic attractions, whereas tourists from southern regions tend to favor natural scenery, and leisure-oriented visits are more concentrated near Nanjing and parts of southwestern China. These spatial differences likely reflect variations in cultural heritage, lifestyle, and accessibility (Wu et al., 2021), as well as broader social dynamics such as the rise of short-distance leisure travel and the increasing role of digital platforms in shaping destination images. From a temporal perspective, the gradual decline in cultural-historic visits and the concurrent rise in leisure and natural visits suggest an ongoing shift in domestic tourism behavior. This trend indicates a move away from predominantly educational or heritage-oriented travel toward more experiential and entertainment-driven forms of mobility (Su, 2023), reflecting changing consumption values and leisure practices in China. Importantly, these observations are derived from origin-city-level data across over 300 cities with weekly resolution, providing a high-resolution baseline that quantitatively situates visitation patterns and ensures comparability across both time and origin cities. As such, RQ1 explicitly serves as a necessary baseline for the subsequent analyses in RQ2 and RQ3, which identify city clusters based on multilayer network similarities and examine the multidimensional factors associated with these visitation regimes.

Stable Visitation Regimes Revealed by Multilayer Networks (RQ2)

For RQ2, the multilayer network-based community detection identifies two dominant and temporally stable clusters of origin cities. Unlike traditional approaches that rely on fixed temporal aggregation, the multilayer framework allows similarities in visitation patterns to be traced continuously across weeks, capturing both persistence and variation without imposing arbitrary time windows. This dynamic, layer-wise approach provides more structured and temporally informed groupings than conventional spatial clustering, enabling the quantification of the stability of intercity similarities over time. The persistence of these two major clusters throughout the study period suggests that intercity similarities in visitation behavior are not random but rooted in long-term socio-spatial characteristics. One cluster, consisting mainly of cities in northern China and Guangdong, shows a strong orientation toward cultural-historic attractions. The other cluster, largely concentrated in southern regions, displays a more balanced visitation pattern between cultural-historic and natural scenery attractions. These differences may be linked to historical roles as cultural and administrative centers in the north and more diversified consumption-oriented lifestyles in the south (Cavagnaro et al., 2021; Sofield & Li, 1998). Overall, the findings highlight that tourist mobility reflects deep-seated regional structures rather than short-term fluctuations alone.

Determinants of Attraction Visitation Patterns (RQ3)

To address RQ3, we examine how city-level characteristics are associated with stable visitation regimes using logistic regression. Given that approximately 92% of cities exhibit temporally stable community memberships, the analysis focuses on explaining differences between two dominant groups: a cultural-historic-oriented cluster and a more balanced cultural-natural cluster. Cities with higher restaurant density, greater distance from Nanjing, higher per capita GDP, and stronger Baidu search intensity related to Nanjing are more likely to belong to the cultural-historic-oriented group. This pattern suggests that tourists from distant and economically stronger cities may prioritize well-known cultural-historic sites to maximize perceived trip value under higher travel costs (Kong, 2007). In some regions, such as Xinjiang, higher per capita GDP is also associated with resource-based economic structures and lower population density, which may reinforce selective, landmark-oriented travel choices (Pannell & Schmidt, 2006).

In contrast, cities located southeast of Nanjing, with higher hotel density and a larger share of younger and working-age populations, are more likely to fall into the balanced visitation group. Younger travelers tend to favor flexible and experience-oriented activities (Buffa, 2015), while a well-developed local accommodation sector may reduce the attractiveness of similar urban attractions elsewhere and increase interest in diverse natural landscapes (Vaz, 2007). Geographic proximity and cultural similarity may also facilitate shorter, multi-purpose trips that combine cultural and natural experiences (Yang et al., 2019). Together, these results demonstrate that tourist mobility patterns are shaped by an interplay of material constraints (distance, facilities) and symbolic drivers (heritage value, digital attention), bridging physical and digital dimensions of urban tourism.

Policy Implications

The findings offer several policy-relevant insights. First, the identification of stable visitation regimes suggests that destination management strategies should account for persistent regional differences rather than relying solely on short-term demand fluctuations. Cities that consistently attract culturally oriented tourists may benefit from continued investment in heritage conservation, interpretation, and digital storytelling, while cities serving more experience-oriented tourists could prioritize integrated cultural-natural tourism products. Second, the strong role of digital attention highlights the importance of online information environments in shaping physical mobility. Destination marketing organizations should strategically manage online content and search visibility to better align digital narratives with targeted visitor groups. Finally, understanding that different origin cities exhibit stable and predictable visitation regimes enables more differentiated intercity tourism cooperation. Policies encouraging coordinated tourism development across regions with complementary visitation patterns may help reduce congestion at iconic sites while promoting more balanced spatial distribution of tourist flows.

Limitations and Future Research

Several limitations should be acknowledged. Focusing on Nanjing as a single destination limits the generalizability of the findings, and the two-year observation period cannot fully capture long-term structural changes or post-pandemic shifts in tourism behavior. Future research could extend this framework to multiple destinations across different cultural and geographic contexts, incorporate longer time spans, and explore how major shocks, such as public health crises or platform-driven tourism trends, reshape the stability and diversity of visitation patterns.

Moreover, future studies could expand the set of network metrics used to analyze temporal multilayer networks, including clustering coefficients, modularity, temporal motifs, inter-layer correlation, and edge persistence, to provide a more comprehensive quantification of network dynamics and their relationship with holidays, seasonal trends, and other temporal fluctuations. In addition, systematic analysis of seasonal variations, such as comparing summer, autumn, winter, and spring periods, could help identify shifts in intercity attraction visitation patterns and uncover temporal drivers beyond the holiday calendar, complementing the current focus on origin-city-level differences in attraction visitation.

Finally, the small proportion of cities that change community membership over time represents an important avenue for future research, as investigating the causes and characteristics of these dynamic cities could provide further insights into emerging trends, regional shifts, or the impact of policy and infrastructure changes on tourist visitation behavior. Future studies could also examine the mechanisms through which digital human activity, such as online search or platform engagement, shapes tourist behavior, including how information-seeking, perceived destination attractiveness, and planning strategies interact with intercity visitation patterns.

Conclusion

This study proposes a novel analytical framework to examine origin-city-level differences in attraction visitation patterns by integrating multilayer network analysis, community detection, and socioeconomic modeling. By focusing on attraction-specific visitation patterns rather than aggregate flows, the analysis reveals how tourists from different cities engage with destinations in structurally distinct and temporally stable ways. The results demonstrate that attraction visitation patterns are characterized by persistent regional regimes shaped by long-term socio-spatial structures, economic conditions, demographic composition, and digital engagement. By transforming complex weekly community-detection outcomes into stable city-level visitation regimes through hierarchical clustering, the study provides a methodologically robust bridge between temporal mobility dynamics and cross-sectional explanatory analysis. These findings also have practical implications for destination management and urban policy. The identification of stable attraction visitation regimes suggests that tourism strategies should move beyond uniform promotion and instead be tailored to the dominant visitation profiles of different origin regions. In addition, the observed role of digital engagement highlights the need for coordinated digital and physical planning in tourism and urban governance in the future.

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Declarations

Competing interests The authors declare no competing interests.

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