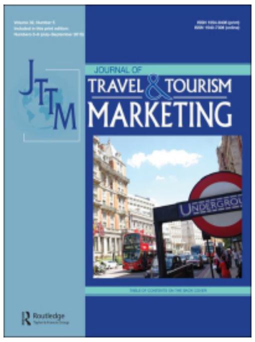

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Understanding seasonal and diurnal variations of inter-city tourism destination network

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ABSTRACT
This study characterizes a destination network based on travel flow. Although the tourism literature has mostly discussed the static configurations of network structures, this study presents a dynamic destination network considering four seasons and daily periods. Given the advancement of connected technology, mobile sensor big data collected from international travelers visiting Korea were analyzed to explore movement behaviors across 250 cities in the country. Results demonstrate the dynamics of complex network systems in tourism destinations over time, such as seasons and diurnal variations. Its findings are crucial for developing vibrant destination management and contextual marketing.

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Network science; dynamics of destination network; tourism big data; mobile data

Introduction

Tourism big data have received sustained attention from tourism academics and industry practitioners. The advancement of information technology, such as social media (e.g., Foursquare, Facebook, and Tripadvisor) and mobile technology, provides destination marketing organizations (DMOs) with unprecedented opportunities to improve their understanding of travel behavior and develop personalized marketing (J. Li et al., 2018). In particular, mobile sensor data offer a rich source of fine-grained spatial and temporal information about travelers while visiting a certain city, state, or country. This feature of mobile data enables tourism scholars to overcome the drawbacks of traditional methods, such as surveys and interviews (e.g., costly and high reliance on tourist recall) and geotagged information on social media (e.g., data sparsity and potential sample bias; Park et al., 2020). The development of mobile technology considerably accelerates the study of tourism, particularly on travel mobility associated with human mobility.

The tourism literature has introduced and applied network science, an innovative discipline that facilitates the characterization of complex systems (Baggio et al., 2010). In network science terminology, a tourism destination can be regarded as a complex network that consists of nodes (i.e., attractions or cities that travelers visit) and edges (i.e., travel flow that links departure and destination cities; Xu, Li, Belyi et al., 2021). This study refers to destination networks as networks between destinations, which represent the configuration of nodes indicating cities that travelers visited with linkages connecting nodes by travel movements (Asero et al., 2016; Sainaghi & Baggio, 2017). The extant literature on network science has mostly discussed the static configurations of network structures, focusing on the spatial dimension of travel mobility and destination networks, such as global airport networks (Guimera et al., 2005), business networks that assess hotel performance (Sainaghi & Baggio, 2014), and destination communities (Xu et al., 2021). However, the literature on modern network science has identified dynamic network structures associated with time; these structures highlight the importance of temporal dimensions in characterizing network systems and labeling time-varying networks (Barabási, 2013a; Karsai et al., 2014). That is, destination networks are not constant; they change over time in response to dynamic travel flows. This argument is closely related to common phenomena in tourism, such as destination demand variations (Rosselló & Sansó, 2017) and differences in travel motivations and behaviors over time (Lu et al., 2016; L. Yang et al., 2017). Nevertheless, studies on network science in tourism have argued a uniform probability of a static network.

The limited tourism research can be attributed to limited data that comprehensively reflects travel flow across different temporal dimensions. The advancement

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of mobile technology enables tourism researchers to reduce spatial and temporal constraints and understand travel movement patterns better. Accordingly, the objective of the current study, which analyzes big mobile data, is to explore the vibrant structures of destinations based on the temporal travel flow of international visitors to the Republic of Korea (hereafter Korea). Specifically, the present study aims to understand, at an inter-city scale, the seasonal (i.e., spring, summer, fall, and winter), and diurnal variations (i.e., morning, afternoon/evening, and night) of tourism network structures by analyzing travel flow through 250 cities in Korea.

The current study makes important contributions to the tourism literature on travel mobility and network science. It initiates a novel approach to investigating tourism big data that integrates travel mobility and dynamic networks from different temporal dimensions. As a result, this study quantitatively characterizes the dynamics of complex systems in tourism destinations (Pavlovich, 2014) instead of presenting a stationary structure of destination networks. Its findings are crucial for developing dynamic destination management and contextual marketing, which may develop customized destination planning and improve visitor experiences.

Literature review

Network science for tourism research

Network science is an interdisciplinary area that studies the relationships or interactions among entities. These entities are frequently represented as nodes in a network, and connections between nodes are represented as links or edges (Barabási, 2013a). Networks are powerful representations of many real-world phenomena; thus, the field has been expanding rapidly in the past two decades (Vespignani, 2018), with a considerable number of studies on different spatial and social systems. Many of these studies have investigated interactions between places or locations (Batty, 2013) using observations of human movements or social connections. These studies have identified important properties of location-based social networks (Eagle et al., 2010; Ratti et al., 2010; Scellato et al., 2011), intra-urban human movement patterns (Zhang et al., 2018), and global mobility and migration patterns (Belyi et al., 2017; Hawelka et al., 2014). The aforementioned studies have leveraged a variety of human activity datasets, such as mobile phone records, geotagged social media, smart card transactions, and taxi GPS trajectories.

Compared with other disciplines (e.g., transportation and urban study), the adoption of network science approaches in tourism is still at an early stage. However, the number of such studies is gradually increasing. Scott et al. (2008) examined the interactions of tourism organizations within each destination using information flows between key stakeholders in four Australian destinations. They demonstrated the usability of network analysis in proving the structure and cohesiveness of destinations. These authors suggested that network analysis is beneficial for tourism researchers in comprehending the entire configuration of a destination rather than focusing on a single element. Baggio et al. (2010) applied network science approaches to understand the effect of network topology on information diffusion and its implications for stakeholder cohesion. The dynamic approach of network science exhibited the positive influences of stakeholder cohesion and adaptive capacity on information diffusion. In addition to understanding a destination network through organizational relationships, Shih (2006) used the survey method to document the travel itinerary of visitors to Nantou, Taiwan. This study applied a collection of network science indicators (e.g., degree centrality, betweenness centrality, and structural holes) to quantify spatial interactions among destinations in the city. Miguéns and Mendes (2008) analyzed a dataset generated by the World Tourism Organization that captured the tourist arrivals of 208 countries in 2004. The authors found a scale-free behavior in the connectivity between tourism destinations and discussed its relationship with countries' socioeconomic and technological developments.

Furthermore, network science approaches have been adopted to determine whether the role of a destination is central or peripheral within a network. The argument is that tourist mobility influences the shape, dimension, and structure of tourism networks that exhibit different characteristics, travel behavior, and holiday types of tourists (Asero et al., 2016). Mou et al. (2020) analyzed the digital footprint data of tourists in Qingdao, China. Their study explored the spatial patterns of tourist flows and found an uneven distribution of tourist visits across destinations and the structural hole phenomenon. Xu et al. (2020) analyzed a nationwide mobile positioning dataset that captured the movement patterns of international travelers who visited Korea within 15 days. Their study found a strong heterogeneity of destination attractiveness and the spatial organizations of tourist flows across the country by applying network science approaches.

Although the existing literature has provided productive insights that suggest the structures/dimensions of destination networks, these studies have focused on the dynamics of the spatial dimension. That is, the temporal dimension of tourism networks remains underexplored (Jin et al., 2018). However, the fundamental literature on tourism has suggested varying motivations of travelers who visit destinations during different seasons and periods, referring to variations in travel preferences and experience seeking at a destination (Giachino et al., 2020; Kim & Moosa, 2001). Fuchs et al. (2014) argued that existing studies remain inconclusive concerning the understanding of the role played by time. In this sense, the temporality of tourist activities embedded into large-scale and fine-grained tourism big data has not been fully utilized (J. Li et al., 2018; Xu et al., 2020). Therefore, additional effort is necessary to improve the understanding of the "dynamic evolution of a complex [tourism] network system" (p. 882, Baggio et al., 2010) and large-scale and full tourism networks (Baggio, 2017).

Dynamics in tourism networks

Understanding the dynamics and evolution of networks is an emerging research topic in tourism in general and the domain of network science in particular (Holme, 2015). One of pioneers who proposed the idea of destination evolution, Butler (1998) proposed Tourism Area Life Cycle (TALC) that represents the sequential stages of destinations, whereby they develop and reach their limits of carrying capacity over time. TALC describes that destinations have a life as a product, and this life would proceed through stages over time, including exploration, involvement, development, consolidation, stagnation, and rejuvenation (or decline). The concept of the destination life cycle has been demonstrated by tourism scholars in various tourism contexts, including destinations (Getz, 1992) and attractions/attributes (Cooper & Jackson, 1989).

Gill and Williams (2013) introduced a novel perspective to the issue of destination evolution to continue the debate about the utility and limitation of the TALC. Alternatively, they suggest a concept of evolutionary economic geography (EEG) to understand better the specific mechanisms of destination. EEG discusses how the spatial economy transforms itself via the dynamic processes of economic novelty emerging from the behavior of economic agents, such as individuals and firms (Boschma & Martin, 2010a). EEG has been recognized as an undertaking framework of tourism research to improve understanding of "how" and "why" tourism destinations evolve (Ioannides & Brouder, 2016) and interpret the role of tourism as a way of accumulating capital in destinations and its implications.

Corresponding to the idea of destination evolution, studies to understand the dynamics of tourism networks have been conducted, with nodes or actors in the networks referring to different types of entities. For example, Aarstad et al. (2015) adopted the metric of clustering coefficients to study the temporal evolution of interfirm networks at destinations. They suggested integrated theories of network science, namely, scale-free structures and small world networks, to guide tourism researchers in explaining network dynamics and capturing destination evolution over time. Pavlovich (2003, 2014) visualized the nodal structure of tourism organizations in an icon tourism destination in New Zealand. The author analyzed the evolution of this destination's structure over the years. The transformation of the destination was attributed to institutional and environmental changes. Consequently, Pavlovich depicted the current destination network as more complex, with "multiple nodes and connections with a structural diversity that now includes core tourism attractions; secondary attractions; supporting activities; and a variety of professional, institutional, and governmental agencies" (Pavlovich, 2014, p. 5). Hristov et al. (2018) applied social network analysis (SNA) to understand the structural transformation of a destination leadership network, which is composed predominantly of private sector-led organizations (e.g., the South East Midlands Local Enterprise Partnership, Experience Bedfordshire, and VisitEngland), before and after the introduction of a government tourism policy in England.

In addition to structural changes among the diverse components of tourism, studies that investigated tourism networks from a spatial perspective have also been conducted. Jin et al. (2018) analyzed a user-generated content dataset extracted from an online tourism site to understand destination networks in Nanjing, China. They examined the structural characteristics of destination networks composed of the movements of travelers with varying lengths of stay to explore temporal heterogeneity in tourist movements. Lee and Kim (2018) adopted network metrics, such as degree centrality and the Gini coefficient, to study attraction networks in Seoul, Korea. The metrics were applied over three years to illustrate the spatial structures of approximately 30 attractions in a city destination and assess the dynamic features of attraction networks. Systematically, their study determined the constant growth of the Gini coefficients of degree distribution for shopping tourists' attraction networks compared with the values of general tourists over time. Similarly, Sainaghi and Baggio (2017) adopted degree distribution and the Gini coefficient to study the network structure of tourism destinations in a region in Italy. An algorithm was also applied to (1) measure the complex structure of tourism destinations and (2) detect possible turning points that present the evolution of networks over time.

Research framework

The existing literature on tourism networks has explored the structures of destination networks that comprise various components (e.g., stakeholders) within the destinations and demonstrate structural changes over time because of environmental, technological, economical, and institutional changes. The previous studies have particularly examined travel movement patterns in terms of the time-invariant dimension, which discusses the static structure of the destination network (e.g., Xu, Li, Xue et al., 2021). However, the travel flow is vibrant across different seasons and/or the hour of the day. Seasonality is one of the most pronounced characteristics of tourism, which largely affect travel behaviors. The reason is that travel movement is subject to environmental factors associated with different seasons, weather conditions, and public and school holidays (Cooper et al., 2005). The effects of four seasons on travel demand and flow (Coshall, 2006; Lim & McAleer, 2008) and travel activities and motivations to visit a destination (Bonn et al., 1992) have been identified.

Hagerstrand (1970) proposed time geography, integrating time as a limited resource into the understanding of spatial behavior. That is, space reflecting movement and time indicating participation in activities are substitute resources. The individual's allocation of these resources is the product of personal goals, reflected in "projects" – the series of activities needed to achieve a goal (Hagerstrand, 1982). These constraints, along with the activities derived from individual projects, define an individual's available time and space resources. Built on the time geography, several tourism researchers adopted the time-space prism method to shed lights on the travel movement patterns. They have identified that visiting a travel attraction was largely different according to the hour of the day. Shoval et al. (2011) found that travelers are more likely to visit the Peak (one of popular attractions in Hong Kong) between 11:00, 14:00. Yet, travelers tend to visit Mong Kok (a popular touristic place) either at noon or late in the afternoon (17:00). Variations of visit patterns across the day have been identified in different studies (McKercher et al., 2012). As a result, examining the hour of the day in 24 hours as a temporal dimension is critical to understanding travel flow patterns. This idea corresponds to the literature on destination evolution, emphasizing the importance of examining the spatial aspects and the temporal development of destinations, reflecting the availability of certain tourist services in understanding the structures of destination development (Henning, 2019).

Accordingly, this study applies community detection algorithms as a network science approach to assess the variations of destination networks across the four seasons (i.e., spring, summer, fall, and winter) and daily periods (i.e., morning, afternoon, and night) by analyzing travel flow through 250 cities in Korea. Several clustering methods, such as K-means, density-based spatial clustering of applications with noise, and hierarchical clustering, mainly analyze the point data (e.g., Park et al., 2020; Vu et al., 2018). However, the data reflecting travel movement that consist of flows (or links) connecting the origin and destination is required with the approach to analyzing spatial interactions rather than focusing on frequency or density of points. Therefore, the point-based clustering method is unsuitable for analyzing the flow dataset, and the community detection method that group (or partitioned) the nodes (or destinations) based on the strength of links (or flow between two destinations) is a proper method to address the research purposes (Liu et al., 2015).

Methodology

Mobile flow data set

This study uses large-scale travel flow data of international travelers who visited Korea between January 1 and December 31 2018. The data were collected by one of the largest mobile telecommunication companies in Korea. Recognizing that Korea consists of 250 districts and cities (hereafter denoted as "city") (see Appendix I), our data sets include (1) spatial information about travel flows between origins (i.e., the cities travelers depart from) and destinations (i.e., the cities travelers arrive at), (2) temporal information in hourly dimensions, and (3) number of tourists associated with travel flows in spatial and temporal dimensions.

Table 1 shows an example of the data format. On the basis of the nominal data denoting origin and destination cities, we identified the central coordinates (i.e., latitude and longitude) of each of the 250 cities and utilized them

Table 1. Example of dataset.

Date	Time	Origin*	Destination*	Nationality	Volume of travel flow
2018–01-01	00	1	2	1	70.5
2018–01-01	00	1	3	1	100.3
2018–01-01	00	1	4	1	17.8
.	.	.	.	.	.
.	.	.	.	.	.
.	.	.	.	.	.
2018–12-31	23	250	249	173	53.5

Note: *Origin/Destination refers to the nominal scale of data naming places. This study defines international travelers as inbound visitors who used mobile roaming services in Korea or Korea sim cards. Overall, the dataset provides a fine-grained view and massive amount of tourist mobility in time and space.

for further data analyses. That is, the city coordinates refer to the nodes in the network analysis, and the travel flows between the cities denote edges connecting the nodes. The volume of travel flow is the so-called weight of a connection. Korea has three key mobile service providers. The volume of travel flow in the last column of Table 1 indicates the weighted statistics based on the relative market share of the telecommunication company for the roaming services in Korea. The data set has been collected on an hourly basis, which captures travel mobility behaviors of international travelers from 173 different nationalities for every hour in an entire calendar year. This study defines international travelers as inbound visitors who used mobile roaming services in Korea or Korea sim cards and visited Korea not exceeding 12 months. Overall, the dataset provides a fine-grained view and a massive amount of tourist mobility data in time and space dimensions.

Data analysis

This study constructed two types of graphs (directed and undirected) to reveal the characteristics of tourist flows within Korea. A directed graph $G = (V, E)$, where V is a set of vertices (or nodes) and E is the edge between vertices, is formed based on city-level tourist flows. In the graph G, each vertex $v_i \in V$ denotes a city in Korea, and an edge $e_{i,j} \in E$ stands for the tourist flow from city v_i to city v_j. The weight of an edge $w_{i,j}$ represents the volume of tourists that flows from city i to city j.The strength matrix is introduced to measure the properties of cities quantitatively. The strength of a vertex is an extension of the nodal degree in a weighted network (Barrat et al., 2004). The in-strength and out-strength of a given city a are defined as follows:

$$s(a)_{in} = \sum_{e_{i,a} \in V} w_{i,a} \tag{1}$$

$$s(a)_{out} = \sum_{e_{a,j} \in V} w_{a,j} \tag{2}$$

The in-strength ($s(a)_{in}$) and out-strength ($s(a)_{out}$) are the weighted sums of the edges directed into city a and out from city a, respectively. As a result, the total strength can be obtained by

$$s(a)_{total} = s(a)_{in} + s(a)_{out} \tag{3}$$

where $s_{total,a}$ indicates the total tourist flow through city a.

In the undirected graph, the directionality of edges was ignored to study the level of overall interactions between vertices. The undirected graph $G' = (V, E')$ has the same topology as the directed graph, except that edges with the same ends are combined. For example, $e_{i,j}$ and $e_{j,i}$ are combined as an undirected edge $e'_{i,j}$, where their weights are added to obtain $w'_{i,j}$.

This study then applied a community detection algorithm as a type of network analytics (Fortunato, 2010). The community detection algorithm identifies groups of nodes (or cities) strongly connected among themselves but loosely connected to the rest of the network. These interconnected groups (or cities) are denoted as communities and/or modules in network systems (Z. Yang et al., 2016). This study employed a multilevel clustering algorithm (or community detection algorithm) to detect communities in the undirected graph. In network science, modularity is defined as a measure of the quality of a network's partition into communities (Malliaros & Vazirgiannis, 2013). That is, the modularity of a network indicates the structure of the network partition. Networks with high modularity have strong connections between nodes within the same communities but sparse connections between nodes across communities.

A typical way to measure modularity Q of a network is as follows:

$$Q = \frac{1}{2W} \sum_{e_{i,j}} \left(w'_{i,j} - \frac{s(v_i)s(v_j)}{2W}\right) \delta\left(c_i, c_j\right) \tag{4}$$

where $W = \frac{1}{2}\sum_{i,j}^{w}$ is the total weight of all the edges in the undirected network, c_i and c_j are the community names of v_i and v_j, and $s(v_i)$ and $s(v_j)$ refer to the total strength of node i and node j, respectively (Malliaros & Vazirgiannis, 2013). $\delta(c_i, c_j)$ is a delta function that ensures that modularity is calculated only between vertices within the same community. An increment in modularity denotes a better partition. The working principle of the multilevel clustering algorithm is to merge single vertices step by step to maximize the total modularity. The algorithm stops when all vertices are merged into one community or when the modularity has reached its maximum. The multilevel clustering algorithm was chosen because of its high modularity and high efficiency in dealing with complex graphs (Z. Yang et al., 2016).

With the community detection analysis results, this study quantitatively assessed the similarity of community structures. Specifically, we compared the partitions of the networks obtained from different temporal dimensions, such as between different daily periods and seasons. In categorizing four seasons, spring includes travel flow data for March, April, and May; summer contains data for June, July, and August; fall includes travel flow for September, October, and November; and winter comprises data for December, January, and February. There is no general rule to classify the time zones when categorizing daily periods. Hence, as an initial point, the researchers set up the sunrise time in Korea, which was 5:00 am (WorldData.info, 2022). Then, three categories were equally categorized by eight hours such as morning (5:00–12:59), afternoon/evening (13:00–20:59), and night (21:00–04:59). The dataset has been classified based on these three daily periods and the community detection algorithms have been conducted for each data, respectively.

This study quantified the similarity between groups (or partitions) using normalized mutual information (NMI; Danon et al., 2005). NMI has been developed in the field of information theory and applied to community detection to compare the similarity of community structures (Belyi et al., 2017). NMI compares communities A and B and can be expressed as follows:

$$NMI = \frac{-2\sum_{i=1}^{C_A}\sum_{j=1}^{C_B} N_{ij}\log\left(\frac{N_{ij}N}{N_i^A N_j^B}\right)}{\sum_{i=1}^{C_A} N_i^A\log\left(\frac{N_i^A}{N}\right)+\sum_{j=1}^{C_B} N_j^B\log\left(\frac{N_j^B}{N}\right)} \quad (5)$$

where C_A and C_B refer to the number of communities in each group (or partition), N_{ij} refers to the number of nodes classified as belonging to community i in group A and community j in group B, and N denotes the total number of nodes. NMI ranges from 0 to 1, and the higher the value is, the more similar the partitions are.

Results

Descriptive statistics

Figure 1 presents the total volume of travel flow moving from one city to another across 12 months. It intuitively suggests the existence of time-varying mobility patterns. International travelers are more likely to visit Korea during the spring and early summer than during the fall and winter. Most people are traveling between cities in April, followed by March, June, and May.

Distribution of node strength across the four seasons

In this section, we analyzed the distribution of network degrees in the destinations. Degree refers to the number of links among the 250 cities estimated by travel flow. The degree can range from 0 (no record of travel flow to a particular city) to 249 (the city links to all other 249 cities). Calculating the Kolmogorov-Smirnov distance (Alstott et al., 2014), the network distribution of degree can be approximated by a log-normal distribution from all four seasons, implying heterogeneity in destination (or city) connectivity or interactions. In other words, a few cities connect to many other cities, whereas many cities connect to only a few other cities through travel flow. The degree distributions are dissimilar when looking into the differences across the four seasons visually and statistically (Figure 2). The results are fitted using the Cumulative Log-Normal Probability Distribution Function:

$$F(x) = \frac{1}{2}\left[1 + erf\left(\frac{ln(x)-\mu}{\sigma\sqrt{2}}\right)\right] \quad (6)$$

where x is the number of degrees of nodes, μ is the mean value, and σ is the standard derivation of the distribution. The fitting results show that the σ of each season

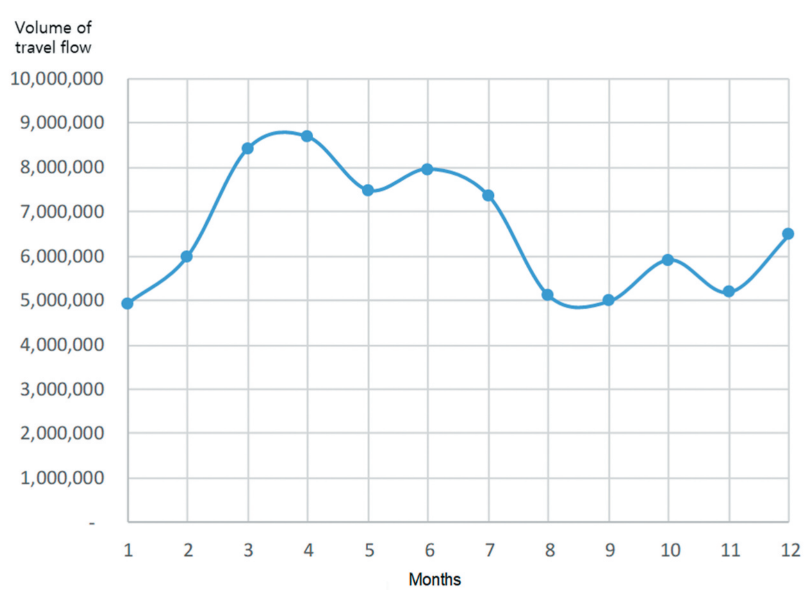

Figure 1. Volume of travel flow that traveled city by city. Note: The volume of travel flow refers to weighted statistics considering market shares of the telecommunication company.

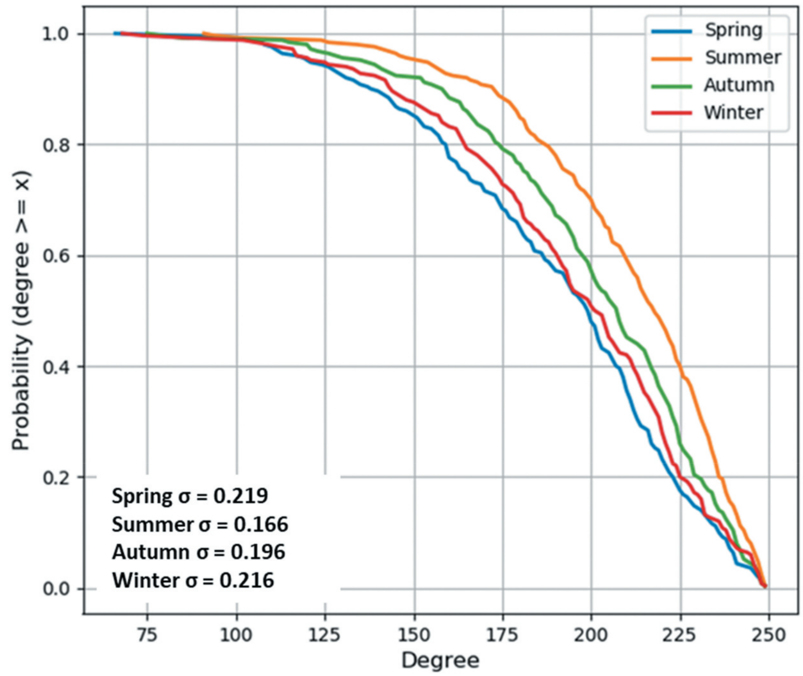

Figure 2. The cumulative probability distributions of node degree across four seasons.

presents different values, such as 0.219, 0.166, 0.196, and 0.216 for spring, summer, autumn, and winter, respectively.

The σ value of the spring flow is higher than the values of other seasons. That is, international travelers who visit Korea in spring are more likely to show concentrated patterns in fewer destinations than those who visit Korea during other seasons. Travelers visiting South Korea in the summer tend to visit diverse cities (or destinations) more actively than people visiting in other seasons. This pattern has been observed on the basis of in-strength, referring to the number of visitors at the destination (or city). The σ value of the spring in-strength shows the highest (1.547), followed by those of winter (1.443), autumn (1.415), and summer (1.367). The distributions can be approximated by a log-normal distribution.

Community structure of destination networks across the four seasons

The modularity score from the community detection algorithm has been calculated. The scores vary from 0.49 to 0.52 across the results, reflecting four different seasons, which suggests that the structure of the destination networks across the 250 cities is not random and tends to persist across the four seasons. Figure 3 shows the inter-quartile box plots of the community size distributions, indicating the total number of nodes (or cities) within each community. Overall, the results of all four seasons present skewed distributions. The median of community size ranges from 27 (winter) to 43.5 (summer). While the median of community size is the highest in summer, the maximum community size is 70 in autumn and winter. The range of quantile distributions also varies between the four seasons. The community size shows a larger variance in spring (SD = 23.2) than in the other three seasons, suggesting that travelers' movements in spring could be highly concentrated in certain regions (e.g., small communities) but dispersed in other areas (e.g., large communities). This finding is consistent with the results of modularity.

In addition to the dynamic structure of network communities, the results reveal that the number of communities (or spatial clusters) differs across the four seasons. Destination networks derived from travel flow comprise eight communities in spring, six in summer and autumn, and seven in winter (see, Figure 4). Variations are distinct among the seasonal networks, suggesting that destination networks are generated in different spatial configurations according to the different seasons. For networks in spring, shown in Figure 4a, Seoul (the capital of Korea) is divided into two separate groups: areas north (C3) and south (C7) of the river Han. A community that covered the middle west area in spring extended in summer to integrate the middle west and east areas of Korea (C1). Given the high temperatures in summer, travelers are more likely to show inclusive movement patterns across the west and east seas, potentially seeking ocean activities. The community networks in the autumn seem

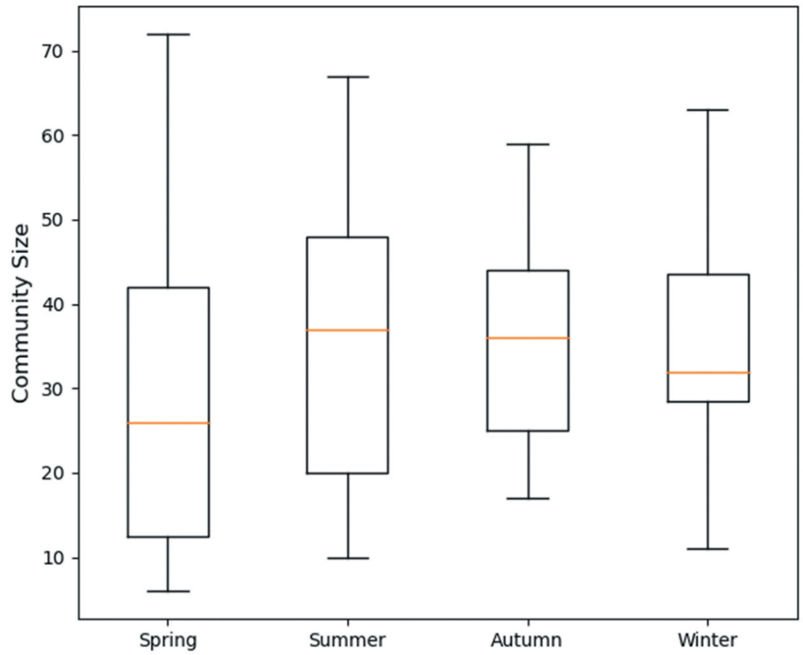

Figure 3. Community size across four seasons.

similar to those in the spring, apart from the community structure in Seoul, where it appears as a single group (C3). The destination networks in winter have a condensed community (i.e., C7), including the southeast sea area (Figure 4d). The community reflecting the northeast areas (C2) seems to be extended vertically. This pattern can be explained by local factors, with famous ski resorts located in the C2 area, such as Gangneung-si and Sokcho-si. International travelers are likely to visit cities within this community for winter sports activities. In addition to the visual comparisons of dynamic community structures, we quantitatively estimated the community similarity across the four seasons by applying NMI. As shown in Table 2, the similarity score of the community structures between the summer and the winter is the lowest, which means that the configurations of destination networks are largely heterogeneous and dynamic between the seasons. That is, the travel movements of people who visit South Korea are significantly different between the two seasons.

Node strength distribution across different daily periods

This section presents the results of time-varying destination networks across different daily periods. Figure 5 presents the degree distributions for three different periods (the blue line for 5:00 to 12:59, the orange line for 13:00 to 20:59, and the green line for 21:00 to 4:59). Consistent with the results of seasonal variations, a log-normal distribution can also approximate the degree distributions. Based on the value of σ from the fitted distributions, travelers are less likely to visit other cities in the morning (σ = 4.63 from 5:00 to 12:59), showing concentrations in dedicated areas. Instead, they visit other cities actively during the daytime between 13:00, 20:59 (σ = 5.36).

Concerning in-strength distributions (σ), a consistent pattern (log-normal distribution) is observed. That is, a few cities are competitive in attracting many visitors, whereas many cities draw few people. Furthermore, the attractiveness is dynamic across different daily periods. The variations in in-strength (or attractiveness) are smaller in the morning (σ = 1.36 for 05:00–12:59) than in other periods of the day. The in-strength distributions of the different daytime periods (σ = 1.43 for 13:00–20:59 and 1.57 for 21:00–4:00) seem alike.

Community structure of destination networks across different daily periods

We assessed network structure by applying the community detection algorithm in terms of the modality index, size, and characteristics of the community. The modularity score ranges from 0.46 to 0.54, suggesting that the network structure is not randomly configured but formed with specific statistical patterns.

The different community sizes among the three-time windows are identified in terms of the median and the variance of the community size, such as the distance between the first and the third quartile and the skewness of the distributions (see, Figure 6).

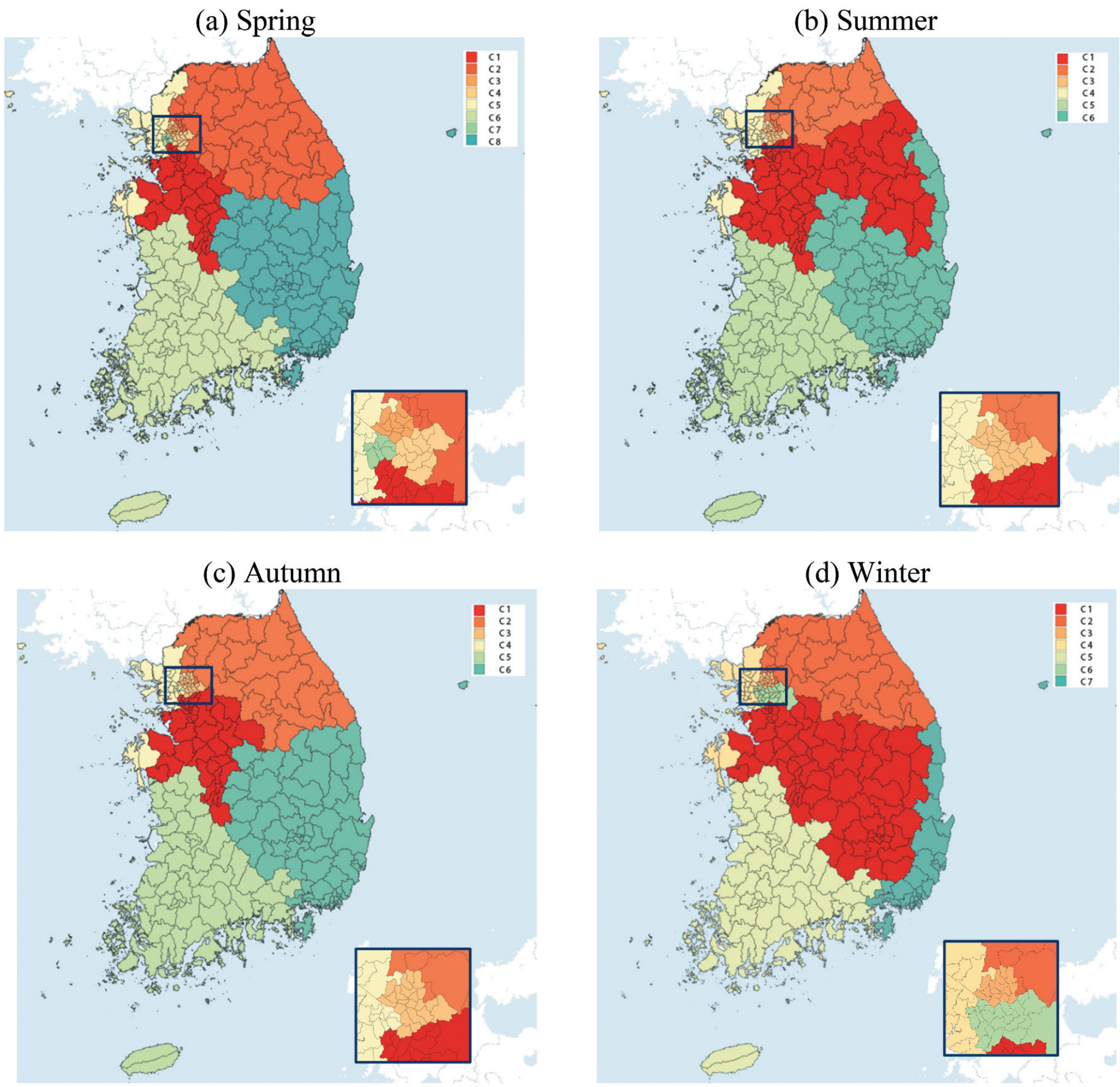

Figure 4. Community detections across four seasons.

Table 2. Community similarity across four seasons.

Season 1	Season 2	NMI
Spring	Summer	0.78
Spring	Autumn	0.86
Spring	Winter	0.77
Summer	Spring	0.78
Summer	Autumn	0.79
Summer	Winter	0.69
Autumn	Spring	0.86
Autumn	Summer	0.79
Autumn	Winter	0.77
Winter	Spring	0.77
Winter	Summer	0.69
Winter	Autumn	0.77

Figure 7 visualizes the structures of the destination networks. While the number of communities representing the destination networks is identical, the spatial configurations are different between the different time windows. This result suggests that travelers (somehow) show dynamic travel flow across different time windows.

We assessed NMI for quantitative measurement. Table 3 shows that the lowest similarity scores of community structures are in the time intervals of 5:00–12:59, 21:00–4:59, meaning that the travel flow passing through different cities mostly differs between morning and night.

Discussion

Tourism destinations are complex systems comprising a large-scale network (Xu, Li, Xue et al., 2021). Complex systems involve the evolution of self-organization, appearing as neither completely regular nor fully random patterns, and they are nonlinear and dynamic. Several tourism studies have suggested that network structure is not static; instead, a tourism destination network exhibits transformation over time (Pavlovich, 2003). However, most studies have applied the

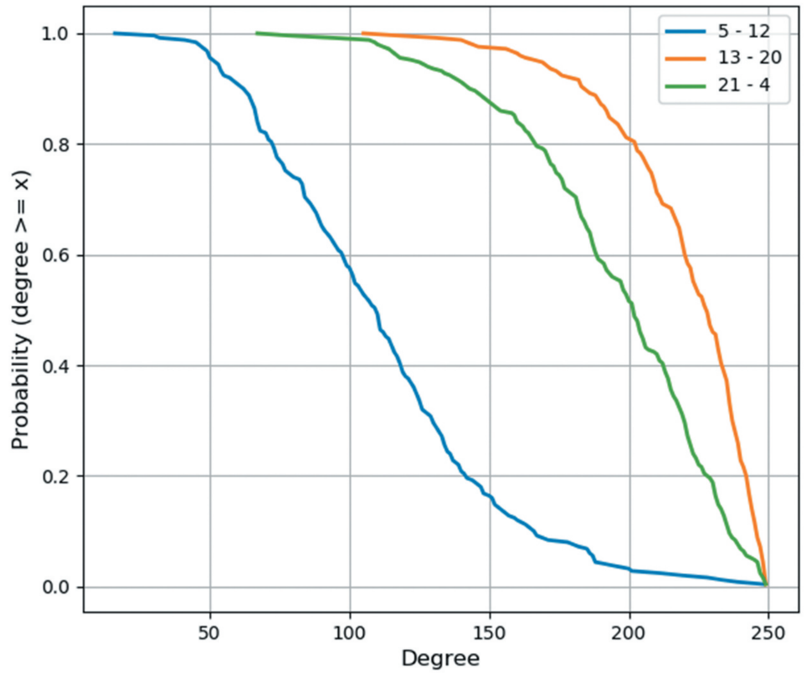

Figure 5. The distributions of node degree across different daily time periods.

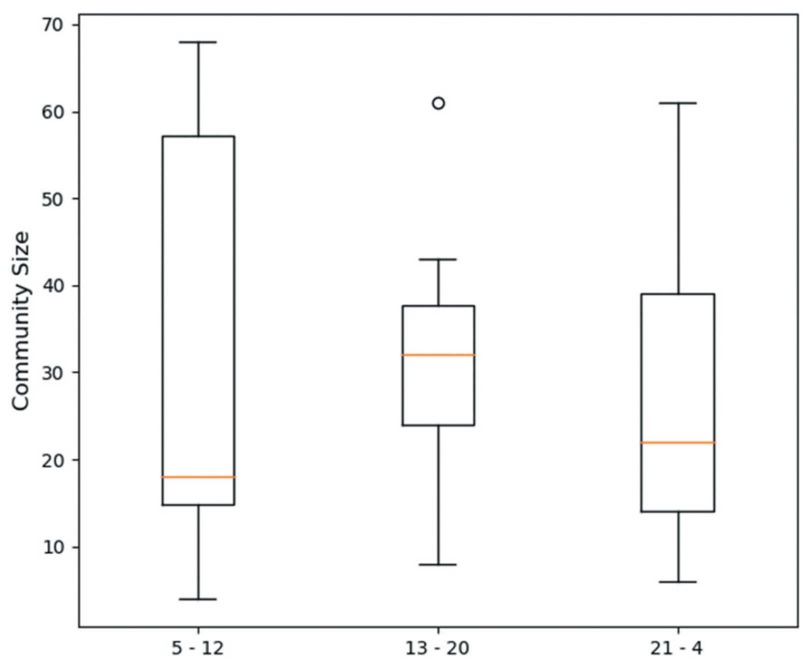

Figure 6. Community sizes of time period categories.

qualitative method and/or focused on a certain city or district (e.g., Pavlovich, 2014). The existing literature on tourism networks has also explored the stagnant structures of destination networks associated with interactions among various components (e.g., stakeholders) with a lack of consideration of temporal dimension (Aarstad et al., 2015; Hristov et al., 2018). The current study addressed the research gap in the relevant tourism literature by analyzing mobile sensor big data. Specifically, this study applied a community detection algorithm that characterizes destination networks by identifying a subset of networks in the graph with denser connections than the other graphs in the network (Clauset et al., 2009). Given the advantages of big data

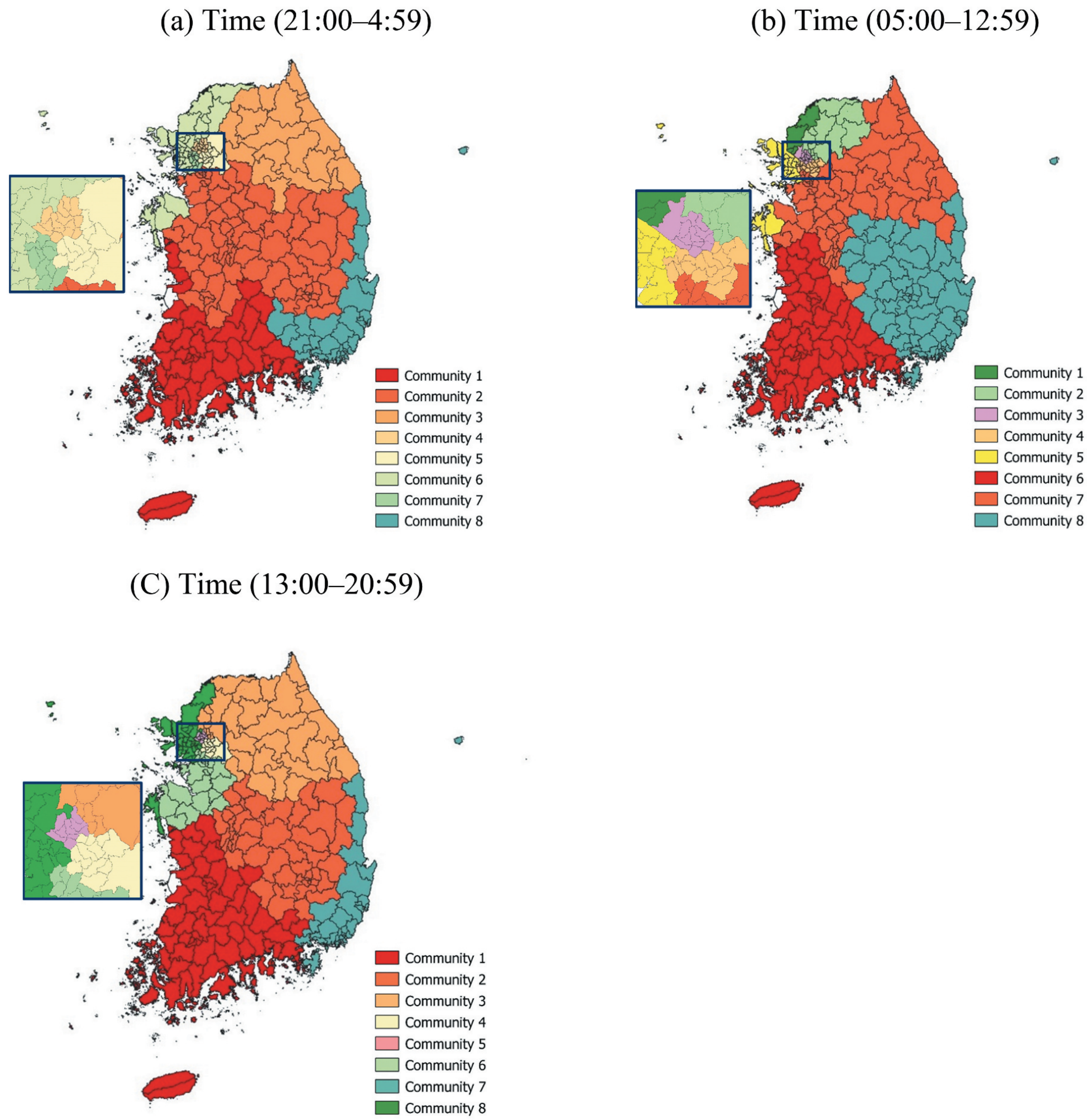

Figure 7. Community detections across different daily time periods.

Table 3. Community similarity between time period categories.

Hour 1	Hour 2	NMI
5:00–12:59	13:00–20:59	0.71
5:00–12:59	21:00–4:59	0.64
13:00–20:59	21:00–4:59	0.71

tourism, this study analyzed travel mobility of international travelers visiting 250 cities in Korea for a year in an hourly basis, and those variations of network structures have been consistently observed in different temporal dimensions, such as the four seasons and diurnal time periods. Consequently, the current study argued that a destination structure is a dynamic and temporal heterogeneity associating with travel mobility, which labels a time-varying tourism network. Therefore, the findings of the current research provide important academic and practical contributions to tourism.

From the perspective of theoretical implications, previous tourism scholars have attempted to explore the structures of tourism networks, such as the properties of inter-organizational networks at a destination (Hede & Stokes, 2009), knowledge transfer (Baggio et al., 2010), and accommodation networks by performance (Sainaghi & Baggio, 2014). Nevertheless, the current study analyzed destination networks on the basis of tourist flows, wherein the cities that travelers have visited refer to vertices and travel movement denotes the edges that connect these vertices (or cities). By using tourism big data, the current research explores "large" tourism networks that consider 250 cities visited by international travelers, ultimately exhibiting the network structure that illustrates their spatial interactions. This approach enables tourism researchers to characterize a comprehensive configuration of a destination network by comparing it with a network that focuses on a single element (or destination; Scott et al., 2008).

Considering an important feature of networks in which network structure is dynamic and evolutionary (Barabási, 2013a), the current study empirically demonstrated the temporal variations of network structures in tourism. The features of a network community reflected by travel flows are heterogeneous over time. This argument is consistent with Jin et al. (2018), who suggested temporal heterogeneity in travel movements, such as length of stay and Park et al. (2022) who demonstrated changes of travel mobility before and after the pandemic. Recognizing the different purposes of travelers who visited Korea across various seasons and during different daily periods, travel flows, including directions and the number of places visited, should be dynamic. Consequently, the findings of the current research obtained using the community detection algorithm prove the different numbers of subnetworks and modularity scores and the different shapes of subnetworks. In contrast with existing studies that have mostly explored different travel demands across various seasons (e.g., Koenig-Lewis & Bischoff, 2005; Lim & McAleer, 2002), the current study demonstrated different movement patterns across varying temporal dimensions as a result of dynamic structures of destination networks (Bernini et al., 2019). This finding is consistent with the Deleuzian concept of networks as rhizomic, suggesting that network connections can be made constantly and that network transformation is a consequence of collaborative connection between destinations (Pavlovich, 2014).

Given the benefits of big data tourism, which cover substantial spatial distributions, the current study investigates dynamic tourism networks that comprise regional interactions. In contrast with previous studies that examined destination networks on the basis of relationships among different stakeholders/organizations, the current study applied tourism mobility across 250 cities in a country and quantitatively exhibited dynamic changes in network structures associated with travel flow over time, labeling time-varying destination networks.

From the methodological perspective, the current study suggests mobile big data analytics at the intercity level, covering an entire country. The present study recognizes the limitations of the GPS with small sample sizes and the restricted spatial coverage within destinations (e.g., a region) or around attractions. Thus, this study suggests using a community detection algorithm at the intercity level and statistically comparing quantitative and qualitative changes in a network structure. Given the existing literature on the complex structure of tourism destinations, which uses mostly qualitative methods or a single quantitative case (Sainaghi & Baggio, 2017), the current study adopts spatial big data analysis, suggesting innovative tourism analytics.

This study provides important implications for DMOs. By understanding the existence of inequality in tourism demands and incomes across different regions (H. Li et al., 2016), the current work suggests the structural formation of destination collaboration that reflects subnetworks (or regional communities). This study provides local tourism organizations with the dynamic features of destination collaboration following different temporal dimensions. That is, rather than the idea that individual DMOs develop their marketing and management strategies, the findings should be beneficial to form destination collaboration with cities in the same clustering and develop regional marketing. Given the variations of network structures across different times, this study can guide the development of differentiated regional marketing across different seasons or any environmental changes, such as climate changes. For example, instead of producing a travel product for a certain city (or destination), tourism marketers can collaborate with cities clustered in the same community to enhance the attractiveness of the regions and provide inclusive travel experiences to visitors. The findings suggest the dynamic formation of regional collaboration according to different temporal dimensions.

Although this study provides important implications, it has several limitations. First, the data analyzed in this study reflect travel behaviors in Korea. Future researchers are suggested to explore travel mobility and the network structures in diverse destinations to verify the generalizability of the findings presenting the time-varying destination networks. Next, this study analyzed mobile sensor data showing travelers' movement behaviors. This study emphasizes the importance of data integration, indicating behavioral and psychological (perceptions) aspects to understand the theoretical reasoning about the dynamic networks better. In this sense, future researchers who adopt a big data approach are strongly advised to obtain information about travelers' experiences through surveys and/or interviews in addition to travel mobility data.

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Appendix