Pattern Recognition of Travel Mobility in a City Destination:

Application of Network Motif Analytics

Abstract

Urban tourism is considered a complex system. Tourists who visit cities have diverse purposes, leading to multifaceted travel behaviors. Understanding travel movement patterns is crucial in developing sustainable planning for urban tourism. Built on network science, this paper discusses twelve key topologies of travel patterns/flow occurring in a city network by applying network motif analytics. The twelve significant types of travel mobility can account for approximately 50% of the total movement patterns. In addition, this study presents variations in travel movement patterns depending on not only different lengths of stay in topological structures of travel mobility, but also relative proportions of each type. As a result, this paper suggests an interdisciplinary approach that adopts the network science method to better understand city travel behaviors. Important methodological and practical implications that could be useful for city destination planners are suggested.

Keywords: Urban tourism; travel mobility; network motif; length of stay; mobile big data analytics

Introduction

Cities that include a variety of things to see and do in an attractive environment are major tourism destinations (Karski 1990). Urban tourism (or city tourism), exploring the phenomenon of city travel, has emerged as a significant and distinctive field of study. This increase in attention leads to the growth of tourism in cities and results in associated policy issues (Pearce 2001). Urban tourism is distinguishable from other types of tourism. For example, tourism is just one of the diverse economic activities in cities that offer ample facilities and infrastructure (e.g., communications, transportations, and services) for travelers as well as local residents. In particular, city tourists tend to have multiple purposes involving intensive use of urban facilities and services (Ashworth and Page 2011). This implies that urban tourism is complex, involving various stakeholders such as business, government, and residential communities, and that diverse elements constitute the characteristics of cities. As a result, urban tourism studies have emphasized urban planning and policymaking processes that make cities sustainable to satisfy not only travel experiences, but also residents' quality of life (Edwards, Griffin, and Hayllar 2008).

The advancement of technology (e.g., mobile phones and social media websites) enables destination marketing organizations (DMOs) to access "big data" and obtain intelligent information about travel behaviors (Li et al. 2018). A smart city and/or smart destination built on big data analytics enables DMOs to comprehensively understand travel movement patterns and manage the efficiency of their resources, such as transportation services and crowd management in cities. Beritelli, Reinhold, and Laesser (2020) have emphasized the importance of understanding travel flow when designing destination management and planning. Insights on travel flow help planners understand tourism as a function in space and refine elaborate tourism production and performance. Based on the nature of cities that contain large multifunctional entities, this study argues that identifying key typologies of travel flow in city tourism can provide a foundation for developing destination design as part of a smart tourism destination (Stienmetz et al. 2020).

Tourism scholars have endeavored to uncover travelers' movement patterns from the perspectives of inter- and intra-destinations. Several methods, such as surveys and GPS, have been applied to collect travel movement data. However, these methods have substantial challenges, including high temporal and financial costs. Social media information (e.g., geotagged photos) allows researchers to cover broader scales and obtain rich contextual information about travelers. Nevertheless, such data can be sparse and irregular in time and space, which could generate biased results (Lo et al. 2011; Martí, Serrano-Estrada, and Nolasco-Cirugeda 2019). Thus, this paper introduces another big data source—mobile sensor data—that potentially overcomes known limitations and enables tourism researchers to discover comprehensive mobility knowledge.

More importantly, this research proposes an innovative discipline, namely, network science, which studies network models based on mathematical theory to investigate, analyze, and characterize network behavior (Newman 2018). It argues that networks (or systems) can be represented by graphs consisting of a group of nodes (vertices) with links between them (edges) based on graph theory (Newman 2003). As part of modern network science, this study particularly highlights *network motif*, which is described as patterns of interconnections or subgraphs that appear in an observed network substantially more often than in compatible randomized networks (Stone, Simberloff, and Artzy-Randrup 2019). Network motifs are subgraphs (small networks) that display a pattern of interactions between nodes in a larger network. Likewise, motility motifs analogous to the idea of motifs in complex network theory (Alon 2007) refer to a set of recurring movement patterns consisting of nodes (places visited) and links (directional paths) representing a large destination network (Su et al. 2020).

Understanding motifs is vital because they may expose functional properties based on the structural characteristics of a network system. This idea can be applied to better understand travel mobility at the destination. The current literature on travel movement has largely applied descriptive analytics rather than scientific statistical methods. This makes it hard to test the reliability and validity of the travel movement patterns that have been identified. The studies using big data analytics have mainly adopted an idea of pattern recognition algorithm, which primarily discovers dyadic spatial movements. Furthermore, a number of studies have applied social network analysis to reveal the travel flows (e.g., Leung et al. 2012; Peng et al. 2016). Nevertheless, the approach of social network analysis has limitations that make it difficult to capture directional movement and to statistically formulate sequential movement patterns. The network motif method, however, enables tourism researchers to uncover subgraphs (travel patterns) that appear in an observed network statistically more recurrent than in randomized patterns. As a result, the travel patterns obtained from network motifs facilitate portraying the flow network in a compact way by using typologies that comprise vertices and edges.

Furthermore, unlike daily human mobility (Cao, Li, Tu, and Wang 2019; Schneider et al. 2013; Su et al. 2020), length of stay (LOS) at destinations is critical in exploring travel movement because it can be regarded as a temporal constraint that mostly affects travelers' spatial behaviors at the destination (Oppermann 1997). Indeed, as LOS differs, spatial dispersion from the main gateways (or major tourist attractions) varies (Kang 2016).

Therefore, the main purposes of this paper are (1) to determine topological patterns of travel mobility by applying network motif analytics and (2) to reveal different patterns of travel typology according to different LOSs. Findings derived from analyzing high-resolution mobile sensor big data in a city destination—Seoul, Republic of Korea—are critical for tourism knowledge, by suggesting a modern approach to network science, network motif analytics. The application of network motifs derived from biology systems to research on city travel behavior suggests an interdisciplinary approach. This study also suggests an innovative method to discover key travel movement patterns from the perspective of network science, shedding light on complex urban destination systems. Indeed, network motif–based analysis enables researchers to quantitatively verify the degree of temporal and spatial pattern regularity, described as simple rules in a destination underlying complex travel mobility. Indeed, this study reveals key typologies of travel mobility patterns that consider the interconnection of places visited by travelers at an individual level, unlike existing relevant findings that explore the collective nature of travel movement analysis (e.g., Park et al. 2020).

Literature Review

Network Science and Network Motif

Network science states that most systems in nature can be depicted by complex networks consisting of nodes (or vertices) and links (or edges) connecting nodes (Baggio 2017). Complex networks enable scholars to address important research problems by discussing the formation and dynamic structure of a network and the effect of the network structure on dynamic network behaviors, which traditional studies have overlooked (Wang and Chen 2003). The underlying assumption of network science is built on the idea that interactional patterns (or processes) between individuals/objects of the principal system can be entrenched in a regular and universal structure, such as a Euclidean lattice referring to the length of a line segment between two spatial points. The key aim of network science is to identify unifying principles that facilitate a description of the fundamental features being uncovered and form dynamic behaviors in the network system to better understand not only the topological objects of a network, but also the framework from which dynamical systems are derived (Newman 2018). Along with technological advancement (e.g., increasing size and quality of data and high-performance computing process), recent discoveries in complex networks suggest observations of large-scale complex networks called scale-free networks; that is, the distribution of connectivity (or degree) presents a power law format: most nodes have extremely few connected links, but a few nodes have numerous connections. A power law signifies no typical degree or scale of a network, hence it is labeled a scale-free network.

The notion of network science has been applied in tourism and hospitality and guides the characterization of the distinctive structure of complex real-world networks (i.e., the whole system and its constituents) involving various types of relationships (Lozano and Gutiérrez 2018; Baggio and Sainaghi 2011). Indeed, a key stream of research that applies network science is that of the mobility patterns of travelers. A tourist's flow can be represented as a directed graph, where a node denotes a visited location, and an edge indicates the movement sequence. Travel flow between countries and cities as well as within cities has been detected in directed and/or undirected networks considering spatial proximity. In this sense, network analysis helps tourism researchers identify the spatial shape of tourism mobility by assessing the network features in a multidestination net (D'Agata, Gozzo, and Tomaselli 2013). In addition to travel behaviors at the country and city levels, several researchers have focused on specific attractions such as natural recreational areas (Orellana et al. 2012) and outdoor recreation activities built on graph theory (Taczanowska et al. 2014). Recent years have seen attempts to integrate various data sources. Belyi et al. (2017) combined three data sources—Twitter, Flickr, and official migration data—and indicated a multilayered network of travel mobility across countries in terms of short- and long-term mobility perspectives.

Indicating remarkably complex networks in various aspects of society, recent literature on network science has suggested that the large-scale properties of a complex network are regulated by smaller constituents—"network motifs" (Stone, Simberloff, and Artzy-Randrup 2019). Indeed, network motifs denote interconnected patterns occurring in complex networks that are notably higher than those in randomized networks (Schneider et al. 2013). Fundamental research by Milo et al. (2002) attempted to go beyond the global features of scale-free networks by understanding the basic structural elements particular to each network class and developing an innovative approach to detecting network motifs consisting of recurring substantial patterns of connections. They applied the network motif algorithm to several networks, including gene regulation, food webs, neuron connectivity, and the World Wide Web and revealed (1) a three-node motif: the feed-forward loop and (2) a four-node motif: bi-fan, which mostly appeared in each network. The notion of network motif was also applied in exploring human mobility (Cao et al. 2019) and transportation (Su et al. 2020). Indeed, Schneider et al. (2013) analyzed mobile phone and survey datasets and detected seventeen unique motifs that explain up to 90% of daily human mobility patterns. Yang et al. (2017) proposed travel motifs by analyzing Flickr data and found tourist behavior patterns; they identified various motifs according to the different numbers of attractions travelers visited. In this sense, tourism literature states that travel movement represents a discrete sequence of movement between places, which characterizes general flow patterns (Bujosa, Riera, and Pons 2015). As a result of its review of relevant literature, this research proposes network motif analytics to determine the structural typologies of travel patterns (or flow) consisting of interconnections between destinations/attractions occurring in tourism networks at numbers that are significantly higher than those in randomized networks.

Spatial-Temporal Tourist Behavior in Urban Destinations

Determining travelers' time–space activity patterns at destinations is crucial to develop an efficient destination management strategy (Bauder and Freytag 2015). Literature on urban tourism and travel behavior has suggested the multi-attraction trip, in which travelers tend to include several attractions and activities in their trip itinerary rather than planning to visit a single attraction or carry out a sole activity (Hunt and Crompton 2008). This is because city travelers seek multiple benefits from their travel (i.e., economic rationalism) and cope with heterogonous preferences, and aim to reduce risk and uncertainty during their trips (Tideswell and Faulkner 1999; Lue, Crompton, and Fesenmaier 1993; Carlisle, Johansen, and Kunc 2016). To accommodate a substantial volume of tourists and provide positive experiences, it is important for DMOs in a city to understand tourists' time–space movement patterns and facilitate their activities by offering context-related information (Edwards and Griffin 2013); this is a fundamental idea of flow-based destination management (Beritelli, Reinhold, and Laesser 2020).

Spatial-temporal behavior refers to the sequential attractions/places that tourists visit within a geographic area (e.g., city, district, state, and country) or their sequential movement in a geographic space, describing travel flow between one attraction and another (Xia and Arrowsmith 2008). That is, the sequence intrinsically encompasses the order (or timing) of people's visits to attractions, and the attractions indicate specific places (or spaces) where people stop over. In this sense, spatial-temporal behavior can be represented as a discrete sequence of movement across places, which characterizes general flow patterns (Bujosa, Riera, and Pons 2015). The literature on human mobility and travel movement consists of two perspectives: that of behavioral aspects focusing on the physical movement of travelers and a cognitive approach that underlies the decision-making process (Caldeira and Kastenholz 2018).

Tourism researchers have used several methods to track travel movement/flow, including not only paper-based surveys such as trip diaries (Zillinger 2007), but also digital traces such as global positioning systems (GPS) and social media platforms (e.g., Flickr and TripAdvisor). This advanced technology enables tourism researchers to identify the time–space activities of travelers and perform different statistical approaches with high accuracy and a large volume of geolocated information (Beeco et al. 2013). For example, García-Palomares, Gutiérrez, and Mínguez (2015) discovered the spatial distribution patterns of international travelers in eight major European cities and demonstrated the usefulness of online photo-sharing platforms to identify the main tourist attractions. Zhao et al. (2018) analyzed mobile tracking data and proposed a fine-grained travel party partition method to determine the number of accompanying tourists. The study presented different spatial and temporal patterns of tourists according to different travel party sizes. Chua et al. (2016) explored Twitter-geotagged information and revealed the spatial, temporal, and demographic characteristics of tourists. Likewise, a study conducted by Vu, Li, Law, and Zhang (2018) analyzed digital footprint data from Flickr and applied pattern mining analytics, which suggests sequential movement behaviors in cities around the world. Furthermore, the integration of Twitter check-in data facilitates the identification of travel activity patterns in a city destination (Luo, Vu, Li, and Law 2019).

Besides social media data, tourism researchers have adopted GPS technology, which allows them to passively gather accurate information on the time–space movements of tourists at a fine level (Shoval and Isaacson 2007). McKercher et al. (2012) discovered different visit behaviors between first and repeat visitors to an urban destination. More specifically, while first-time visitors tended to travel more widely all over the destination, repeat travelers tended to restrain their activities to a smaller number of locations. Travel movement tracking via the GPS method has found heterogenous travel behaviors in relation to hotel locations in Hong Kong as a key tourism city (Shoval et al. 2011). These studies focusing on behavioral perspectives have still faced challenges with small sample sizes and limited validity of data (e.g., imprecise information about location and context) as well as relying on a descriptive approach (Shoval et al. 2015). As a method to overcome these restrictions, the rapid advancement of mobile technology helps tourism researchers obtain the comprehensive paths of travelers in both spatial and temporal facets from a large number of mobile users (or travelers). Raun, Ahas, and Tiru (2016) examined travel flows in Estonia and identified dynamic behaviors of visitors according to different seasons. A study by Zhao et al. (2018) investigated mobile tracking data in Xi'an City, China, and suggested different travel movement patterns in association with varying travel party sizes. Furthermore, Park et al. (2020) explored mobile sensor big data and identified tourism hotspots in cities, across which they discovered vital travel mobility patterns. They essentially highlighted the importance of understanding travel flow in designing tourism planning/management.

Tourism studies have identified numerous factors determining tourists' spatial behaviors (Lau and McKercher 2006), such as individual factors (e.g., destination familiarity, past experiences, and travel lifestyle) and environmental/physical factors (e.g., distribution of attractions and time). Among these factors, this study focuses on LOS as an element of time constraints. Oppermann (1994) found differences in travelers' spatial behaviors according to different LOSs: indeed, as LOS increases, spatial dispersion from the main gateways (or major tourist attractions) expands. Similarly, Lee, Morrison, and O'Leary (2006) concluded that LOS that defines economic values is an important factor affecting activity patterns and travel expenditure at the destination. Wu and Carson (2008) regarded LOS as a temporal dimension and found structures of travel flow illustrating the gradual dispersion of international travelers at the destinations. Several researchers have recognized LOS as a constraint to spatial travel behaviors (Kang 2016). Shoval (2012) considered LOS as a capability constraint that may affect the spectrum of opportunities for tourists. Likewise, when travelers have limited time during their trips, space is more conserved (Fennell 1996). Differences in the spatial structure (or association) of tourist attractions based on spatial network analysis were discovered according to different LOSs (e.g., short, medium, and long). The extant literature found different spatial dispersions (or distances) and numbers of attractions that travelers visit across different LOSs. Thus, an understanding of different travel flows considering LOS in urban tourism is critical for developing network typology in travel mobility.

Methodology

Study Area

This research investigates Seoul, the capital of South Korea, which is the largest metropolis in the country (see Figure 1). Based on GDP, Seoul is the fourth largest metropolitan economy (US$635 billion) in the world after Tokyo, New York City, and Los Angeles. Seoul includes a number of historic, natural, and modern attractions, and is the city most visited by international travelers (approximately 12,451,891 in 2015) in South Korea (Korea Tourism Organization, 2019).

[Please insert Figure 1 about here]

Features of Mobile Positioning Dataset

Researchers were able to collaborate on a mobile big data project with one of the largest telecommunication companies in South Korea, allowing a researcher to access a massive-scale mobile positioning dataset. As opposed to other types of mobile sensor data such as call detail records and mobile signaling data that records mobile signals at discrete time points (Zhao et al. 2016), this data set contains the full records that traced mobile users' digital footprints during visits in South Korea. This dataset contains the trajectory of 90,140 international travelers who visited Seoul during a period of 15 days (August 1, 2018–August 15, 2018), comprising a total of 3,694,856 data points. An example of the dataset is shown in Table 1.

[Please insert Table 1 about here]

Each record in the mobile positioning dataset represents a period of stay of a user at certain locations. The record contains user information (unique user ID and nationality) as well as location (longitude and latitude) and time (date, start time, and end time) information. Location information in the dataset was tracked at the level of cellphone towers. Start and end times indicate the tourist's stay period within the coverage of a cellphone tower. Time intervals between consecutive records provide information on tourist movement between places visited because the dataset only records the mobile phone when it continually connects to an individual cellphone tower for over 9 minutes. For example, according to the first two rows in Table 1, User R000001 visited location positions of cellphone towers such as (longitude = 126.*** and latitude = 37.***) and (longitude = 127.***, latitude = 27.***) between the time windows of [00:14:00–08:57:00] and [09:47:00–10:41:00], respectively. The data imply that a traveler has stayed in the first cellphone tower location (126,***, 37.***) for 8 hours and 43 minutes and then moved to another place managed by a different cellphone tower (127.***, 27.***). The time interval [08:57:00–09:47:00] is assumed to be the moving period of the tourist. Figure 2 presents the individual phone trace.

[Please insert Figure 2 about here]

Once international travelers arrive at the international airport, the location-based system tracks their movements until they leave Seoul (e.g., Figure 2). Thus, the maximum LOS of the digital footprint should be 15 days. The Korea Tourism Organization reports that the average stay duration of international travelers in South Korea is 8.36 days, and approximately 93% of travelers visit South Korea for less than 20 days (Korea Tourism Organization, 2019). Accordingly, it can be said that our datasets include sufficient sample profiles to meet the representativeness of international travelers visiting South Korea.

Data Analysis

Figure 3 illustrates the sequential procedures of tourism big data analytics for network motif analysis. The procedures consist of understanding the structure of mobile positioning data, the trajectory construction, daily trajectory, and motif analysis. Details of each step are described in the following sections.

[Please insert Figure 3 about here]

Structure of mobile positing data

To understand destination network structure, this study measured the distance between each cellphone tower. Based on initial data analytics, it showed that there are total of 6,300 cellphone towers in Seoul. The average distance between each cellphone tower was 156m (142m on median distance). The cellphone tower record can be regarded as nodes in the network motif, and the travel movement between two cellphone towers can be represented as edges in the network motif analysis. This refine-grained network infrastructure of the cellphone tower allowed the researchers to comprehensively identify tourist mobility in both time and space.

Trajectory construction

Trajectory analysis was conducted to assess tourist movement behaviors. Given the nature of mobile positioning data, the individual's sequence of movement can be extracted by tracing all records of cellphone towers visited with the same user ID. The traveling trajectories of visitors can be constructed after sorting the traveling sequence according to their start and end times for every cellphone tower revealed. Each person's time-ordered traveling trajectory can be written as a sequence of cellphone tower visiting records:

T = {R000001: [(CPT1, date1, start1, end1), …, (CPT n, daten, startn, endn)],
R000002: [(CPT 2, date2, start2, end2), …, (CPT m, datem, startm, endm)],
…
R192302: [(CPT x, datex, startx, endx), …, (CPT y, datey, starty, endy)]}

where T denotes trajectory; CPT refers to locations of cellphone towers; date indicates the visiting date; and start and end are the start time and end time of the visits, respectively.

This procedure is fundamental in order to extract the full trajectory information of each traveler combining spatial and temporal information together.

Network Motif analysis

In network science, many complex systems can be represented as networks formed by points and connections between points. These points are called nodes and the connections are known as edges between nodes. In trajectory analysis, tourist movement patterns can also be transformed into a complex network (Schneider et al. 2013). Cellphone tower spots are nodes connected by moving tourists referring to edges.

Network motif analysis simplifies the daily trajectory as a sequence of cellphone tower IDs, which is relabeled in the order of the appearance of the cellphone towers in a person's record on that day. For example,

$$T_1 = [(10,10), (5, 5), (10, 10)]$$

$$T_2 = [(23, 53), (46, 96), (23, 53)],$$

where suppose that the numbers refer to coordinate information (or cellphone towers such as CPT1, CPT2, and CPT3).

This implies that a traveler (T_1) initiates her/his trip in Seoul from the area covered by cellphone tower 1 (coordinate: 10, 10) and visit another place managed by cellphone towers 2 (coordinate: 5, 5). Then, the traveler returns back to the starting point (CPT1) (coordinate: 10, 10). This trajectory can be simplified as an integer sequence:

$$[0, 1, 0].$$

While travelers (T_1 and T_2) have visited different places in their trajectory, their topology of the mobility is identical. That is, it describes that the first and third places (or cellphone towers) travelers visited are same whereas the second spot is different. That is, a daily pattern of the individual traveler shows a morphology as “turning back” with same start and end points of his/her journey. It should also be noticed that travelers may move from one accommodation place to another during daytime. Thus, the first spot and last spot in a daily pattern are not necessarily identical, which is the key difference between our traveler motif study and traditional resident motif studies.

Suppose that a traveler visits Seoul for three days. The daily trajectory has been analyzed for the second day to track their behaviors in 24 hours. Note that this analysis assumes that visitors wake up after 06:00 and return to the hotel before 03:00. Thus, the first cellphone tower record in a day, whose end time is later than 06:00, is treated as the starting point. The last cellphone tower record in a day, whose start time is before 03:00, is regarded as the ending point. Importantly, the motif analysis excludes the trajectory data of certain international travelers who visited Seoul less than a day. These travelers can be regarded as ones who transfer travel to other places. Even further, considering the research purpose to identify daily travel motifs, the restricted behaviors may affect biased mobility intelligences. Based on the above rules, each traveler has $l-1$ motifs, where l is the length of stay (days) that traveler stayed in Seoul. Thus, the total number of motifs is equal to:

$$M_{total} = \sum_{i}^{N} l_i - 1$$

where N is the number of travelers and l_i is traveler i's length of stay in Seoul.

The representation of the simplified daily motifs is an integer sequence starting from 0, which is transferred from daily trajectories. The first step of extracting a motif is to find out all different CPTs in a daily trajectory. Then, these CPTs are labeled with increasing integers (starting from 0) according to their order of appearance in the trajectory. Finally, an integer sequence is constructed by replacing CPTs with their integer labels. Two motifs may contain same integers, but a same integer unnecessarily directs to the same CPT.

After motif extraction, there exist motifs sharing same integer sequence. To compute the frequency of each motif and select out the most common traveling patterns of foreign tourists, the occurrence of every motif is calculated using the equation:

$$M_k = \sum_{i}^{N} \sum_{j}^{l_i - 1} \delta(m_{ij}, m_k)$$

where m_k represents a unique integer sequence, and M_k is the occurrence of m_k in all motifs. N is the number of travelers, l_i is the traveler i's length of stay in Seoul, and m_{ij} is the simplified motif of traveler i on his/her $j+1$'s day of stay in Seoul. $\delta(x, y)$ is a delta function, which is equal to 1 if the two components are identical, otherwise it equals to 0. Then, the frequency of integer sequence m_k is calculated as:

$$f_k = \frac{M_k}{M_{total}}$$

The frequency of every integer sequence is calculated and compared based on the traveler's length of stay and day of stay in Seoul.

Daily trajectory considering Length of Stay (LOS)

Considering that it is the nature of travel mobility for people to have different LOS, it is critical to discern travelers who have various LOS and estimate their daily trajectory accordingly. For example, if tourist A plans to stay in Seoul for 10 days and tourist B wants to visit Seoul for 3 days, travelers' moving trajectories are highly likely to be distinguishable (Jin, Cheng, and Xu 2018, Oppermann 1994). In this case, the daily moving pattern is an appropriate method for analyzing the similarity between trajectories. In previous studies, the Markov chain method was used to study the mobility of local people whose homes are usually regarded as the starting point of their daily movement (Schneider et al. 2013). However, tourists may change their accommodation during their visit, which makes identifying their starting point difficult. More importantly, considering arrival and departure days, travelers' trajectories are largely varied due to variations in their time of arrival to and departure from Seoul. Hence, the researchers focused particularly on certain days when the total trajectory information (24 hours) of travelers was available for the whole day in Seoul.

After calculating the daily motif pattern of every tourist (192,302 tourists), the frequency of motifs was summarized and compared according to different LOS. As a result, the daily motif patterns are written as follows:

M = {R000001: [[0, 1, 0], [0, 1], [0, 1, 2, 0],
R000002: [[0, 1, 2, 3]],
R000003: [[0, 1, 0, 2, 3, 4, 5], [0], [0, 1]],
…
R192302: [[0, 1, 0], [0, 1, 2, 0], [0, 1, 2, 3, 2], [0, 1]]}

where the trajectory within [] refers to daily motif patterns.

Results

Profile of Respondents

Initially, the number of tourists who visited Seoul from August 1, 2018 to August 15, 2018 has been calculated. Two local peaks, namely, 8/3 (Friday) and 8/13 (Sunday), are identified, means that the largest number of international travelers visited Seoul on 8/13, and a local minimum was observed on 8/6 (Monday).

Temporal Movement Patterns

This analysis assesses the percentage of international visitors who traveled to Seoul across 24 hours. The researchers have estimated the number of visitors moving from the location of one cellphone tower to another in hourly time windows, and have divided the result by the total population of visitors staying in Seoul during that period. The result reveals that the moving percentage starts increasing gradually at around 7:00 and rapidly decreases from 21:00 onwards. 70% of the travel movement has taken place between 11:00 and 22:00.

Daily Travel Distance

This section estimated the distribution of the average moving distance of visitors in Seoul. Approximately 47.21% of visitors had a moving distance of 0–5 km. About 85% of travelers moved equal to/or less than 10 km a day for their trips. This suggests that most international travelers tend to move within the daily distance of the basic fare for public transportation (Korea Tourism Organization, 2019).

Successive Records in the Daily Trajectory

The duration of successive records in the visitor daily trajectory demonstrates the daily time a visitor spends moving between spots. The majority of visitors (about 80%) exhibit successive movement equal to/or less than 400 minutes per day with 303 minutes on average. It also reveals that the peak is located at around 250 min/day while visiting Seoul.

Average Visiting Duration for Each Cellphone Tower

This section analyzed the time spent on visiting individual cellphone towers. The mean of visiting duration is 129.5 min. This means that international travelers tend to stay at a cellphone tower, on average, for about 130 minutes for their travel activities. The majority of visitors tended to visit a cellphone tower for between 50 and 60 minutes.

Topological Type of Travel Patterns by Network Motif Analysis

The researchers initially uncovered a total of 172,427 daily trajectories from the mobile sensor data of international travelers who visited Seoul. Among over 170,000 trajectories, this study came up with 31,072 types of travel mobility patterns. As is the nature of scale-free networks (Barabási 2016), a few dominant patterns explain the travel movement behaviors, showing largely skewed distributions of pattern frequencies (see Appendix I). For example, about 51.1% of daily travel patterns showed less than 1%, which means that individual travelers exhibit extremely heterogeneous behaviors.

In order to identify significant travel motifs, the z-score was calculated to assess the variability of entire travel patterns. The z-score is determined by Equation (1):

$$z\ score = \frac{F_G(m) - F_{R,Avg}(m)}{\sigma(F_G(m))}, \quad (1)$$

where, $F_G(m)$ is the frequency of pattern m, $F_R(m)$ indicates the frequency of pattern m in a random graph R, and $F_{R,Avg}(m)$ and $\sigma(F_G(m))$ are the mean and standard deviation of frequency in random networks, respectively.

As a result, the top 38 travel patterns showed a z-score over 1.96 equivalent to 95% probability ($p < 0.05$), demonstrating that the occurrence of travel patterns is substantially higher than those in randomized networks. Of those top 38 travel patterns, however, this study reveals that the top 12 patterns (over 11.38 of z-score) had a frequency of travelers of more than 1%, thereby reflecting 48.9% of the total travel patterns. From this section onwards, daily travel pattern refers to the selected 12 motifs presented in Figure 4. This implies that 0.04% of travel patterns are able to explain approximately half of the entire mobility patterns. Compared to previous studies about daily human mobility, tourist routines are relatively much more diverse than those of the resident motifs analyzed (c.f. Schneider et al., 2013).

[Please insert Figure 4 about here]

In general, international travelers who visit Seoul are likely to visit less than six different places in their daily travel movements. More specifically, about 12% of travelers visit a single place a day (T1). The most popular place for those travelers who visit only one place was regarded as Chungmuro in Jung-gu, an area famous for Korean culture, artists, and the film industry. Assuming the starting point as their accommodation, travelers are likely to visit one (T2 and T3) or two (T4, T5, T8, T10 and T12) additional places, which stands for about 30% of the top mobility patterns together.

For more detailed insights, Table 2 summarizes the features of the 12 topological travel patterns linked to extant tourism theories. Type 1 refers to no movement, where travelers stay in the hotel for the entire day or travel from it within an approximately 200m radius. Type 3 can be named as no movement and a single distant stop with a journey trip greater than 200m from the accommodation locus to a specified attraction or node. Types 2, 4, 6, 8, and 9 are categorized as cycle patterns representing tourists who visited a set of different places one by one and then returned back to the starting location (accommodation) at the end. Tourists in types 2, 4, 6, and 9 tended to visit from one to four different places and then returned back the starting location. More interestingly, Type 8 shows a centralized cycle pattern where tourists visit a specified place and then return back to the starting point, and then they subsequently visit another place and come back to the starting point. In this case, the starting point (or accommodation) can be regarded as a "central" location that includes more than two directed edges. Types of travel patterns such as T3, 5, 7, 10, 11 and 12 signify travel morphology as a "chain", showing that tourists visit places one by one like a chain without turning back to the starting point. Similar to cycle patterns, types 3, 5, 7, and 11 present a consistent pattern but a different number of places visited. Importantly, types 10 and 12 represent mutual dyad chains where tourist movement includes coming and going behaviors in a chain pattern. More specifically, type 10 can be confirmed as an "uplinked mutual dyad chain" where the mutual dyad occurs at the end of chain, and type 12 denotes a "downlinked mutual dyad chain" in which the mutual dyad appears at the beginning of chain (Jackson 2010).

[Please insert Table 2 about here]

Travel Mobility Patterns considering Length of Stay (LOS)

Next, this research explored travel mobility patterns in consideration of LOS. Figure 5 shows the distribution of LOS from 2 to 15 days. Approximately 74% of travelers stayed in Seoul for 3-7 days. Less than 5% of travelers visited Seoul over 7 days in their trips. Then, the researchers calculated the average number of different places (i.e., cellphone towers) visited by tourists with respect to their LOS and days of stay.

[Please insert Figure 5 about here]

Figure 6 presents the average number of places visited (Y axis) consisting of Nth day of the visit (X axis) and length of stay (Z axis). Note that the Nth day of the visit refers to a certain day during the full LOS in Seoul. For example, the case when the Nth day of the visit is 3 and the LOS is 4 days means the average number of places visited on the third day in a total of 4 days visiting Seoul. The pattern presents that travelers are likely to visit the most places on the second day of their stays in Seoul and gradually reduce the numbers of places visited as they stay longer in Seoul. More specifically, the maximum number of cellphone towers visited occurs on the second day for travelers who visit Seoul for a LOS of 5 days. The maximum average is 5.6, which implies that travelers who stay in Seoul for 5 days tend to visit approximately six different places on the second day. The minimum average is 2.62 for the 14th day of a LOS of 15 days. In addition to the number of places visited, this study explores different travel mobility patterns in terms of different LOS.

[Please insert Figure 6 about here]

Note that network motif analysis has been conducted specifically for the second day of a LOS of 3, 4, 5, 6, and 7 days. This is because the second day of the LOS is the date showing the greatest number of places visited as well as involving travelers' full trajectories (24 hours staying in a city) regardless of when travelers arrive or leave Seoul. The travel daily motif analysis is conducted for a LOS of up to 7 days because international travelers who visit Seoul from 3 to 7 days represent around 74%. As a result, considering the selective results to be shown in this paper, the authors decided to show a LOS up to 7 days. Figure 7 presents the daily travel patterns (second day of stay in Seoul) according to different LOSs.

[Please insert Figure 7 about here]

These 12 topological properties of travel mobility can explain approximately 52.7%, 43.3%, 38.1%, 36.2%, and 35.7% of the total motifs for each LOS 3-7. Initially, it reveals that the frequency of travel mobility patterns varies with the LOS. The frequency usually decreases as the LOS increases, which indicates that the mobility diversity of tourists who stay in Seoul for a longer time rises compared with other tourists staying in Seoul for a shorter period. More specifically, those travelers with a LOS of 3, 6, and 7 days show the highest frequency of T1 whereas travelers with a LOS of 4 and 5 days present M2 as the most frequent patterns. This implies that while the results focus on the same second day of visits in Seoul, a heterogeneity of travel mobility patterns has been observed according to different LOS (Kang 2016).

Discussion and Conclusion

The importance of cities is well founded in tourism literature. Cities clearly play a vital role as a key attraction for travelers (Paskaleva-Shapira 2007). Strategic urban destination planning is the crucial component in making cities sustainable for enhancing not only travelers' but also residents' satisfaction (Ben-Dalia, Collins-Kreiner, and Churchman 2013). Advances in transforming large data into meaningful information are essential to improve our understanding of urban destination systems. Beritelli, Reinhold, and Laesser (2020) and Park et al. (2020) have highlighted flow-based destination management and stressed the need to understand the complexity and dynamics of the interplay between visitors and the place. Accordingly, this study explores a city destination as a tourism system that includes complex travel flows consisting of nodes (places visited) and edges (movements between places). This research, in particular, found key discrete travel mobility and patterns by applying network motif analytics at a city destination; it also revealed topological relationships among places travelers visited. In addition, this study suggested variations in travel flow structures in relation to a situational factor, LOS. It explored mobile big data analytics and found twelve topological types of travel mobility that account for 49% of total travel mobility (a total of 31,073 types). Furthermore, travel flow, including number of places visited and significant typologies of travel flow, varies depending on different LOSs. As a result, this study provides important academic contributions to tourism knowledge for urban tourism planning and tourism network science.

Regarding academic implications, this research adopts network science theory as an innovative approach to determining the structure of complex systems in terms of travel mobility (Yang et al. 2010). In particular, this paper applies the network motif algorithm developed from biology to detect overabundant travel patterns (or flow) of interconnections between places/attractions occurring in tourism. Extant tourism studies exploring travel patterns have mainly employed the Markov chain-based approach, or collaborative filtering (Vu et al. 2015), as well as the descriptive method (Shoval et al. 2011). Importantly, however, this research built on network science theory (Newman, Barabási, and Watts 2006) and tourism big data (Li et al. 2018), considered travel flow at a city destination as the real network, and identified essential spatial topological patterns that recur much more frequently than in an ensemble of randomized networks. As a result, the twelve key and discrete types of travel movement patterns explaining 49% of total patterns improve one's understanding of city destination systems and serve as important knowledge in city destination planning development (Ashworth and Page 2011). Compared to literature on human mobility where seventeen daily networks (or mobility patterns) account for 90% of the recorded trips (Schneider et al. 2013), this study demonstrated the diversity and complexity in travel mobility associating dynamic structures of spatial interactions. This study also presents an interdisciplinary approach to integrating a concept/method from the science field into the tourism discipline to produce innovative mobility knowledge, which can potentially address complex challenges in urban tourism (Ashworth and Page 2011; Edwards, Griffin, and Hayllar 2008).

Furthermore, this research demonstrates the significant impact of LOS in understanding travel network motifs. More specifically, from international travelers who visit Seoul, the highest number of places visited tend to occur on the second day of an LOS of five days. More interestingly, looking at the average number of places visited, an inverted U pattern is shown. That is, travelers are likely to visit more places as LOS increases. However, after passing an inflection point (the second day in this study), the number of places travelers visited (or travel distance) decreases. This finding supports the idea that time is a key situational factor that shapes travel behaviors (Jin, Cheng, and Xu 2018; Lau and McKercher 2006) and identifies different structures of topology properties in travel mobility. That is, proportions of certain mobility patterns vary according to different LOSs.

This paper also provides innovative methodological implications. Along with advancements in technology (e.g., mobile technology) which enable researchers to access massive digital footprint data, this research suggests a series of big data analytics for revealing new insights. This study specifically demonstrates the usability of the network motif algorithm in identifying key patterns in complex tourism networks. Contrary to existing studies focusing on the aggregate nature and independence assumption of all trips (e.g., Park et al. 2020; Vu et al. 2018), the method of network motif focuses on the interconnection of visited places at an individual level. Hence, network motif analytics enable tourism researchers to quantitatively identify the topological structure of travel mobility. Furthermore, while most existing literature on travel movement has mainly presented descriptive statistics showing the frequency of movement patterns (e.g., Shoval et al. 2011), this study suggests an innovative methodology to find hidden typologies of travel flow and quantitatively estimate pattern regularity, demonstrating that it is more noticeable than compatible randomized networks. This method should be applicable to other types of big data (e.g., geotagged information from Flickr or Twitter) for future hospitality and tourism research.

The findings of this research should benefit DMOs in developing city destination planning and management strategies. Indeed, it can be suggested that DMOs in Seoul should develop travel products such as travel packages and design new attractions based on the abovementioned twelve mobility patterns. First, this study re-emphasizes the location of accommodations. Given the result that the most popular pattern is to stay/travel within the coverage of a cellphone tower, DMOs are required to review accessibility (or distance) to destination attractions from accommodations. Next, these findings are helpful for developing optimal travel routes that consider the number of places being visited and the associated directions. For example, travel agents who produce packages for Seoul are advised to consider visits to up to five different places including the starting point (i.e., accommodation). This means that the daily recommended travel products should not exceed four different places. Second, the routines need to include both cycle and chain patterns. This issue is closely associated with the efficiency of transportation systems that facilitate intracity movement. It is suggested that DMOs review the structure of the extant transportation system, that is, whether international travelers can easily access facilities by moving within 10 km. DMOs are also required to develop dynamic travel products for travelers who plan different LOSs at the city destination. For example, DMOs should provide the information about destination attractions near the accommodation (within a 150 m radius) on the first day of their itinerary for travelers who stay in Seoul for three or seven days. At present, COVID-19 is having a tremendous influence on tourism demand in general (Yang, Zhang, and Chen 2020) and travel behaviors in particular (Glusac 2020). Some researchers indicated that during COVID-19, people are less likely to use public transport and more likely to walk and cycle, which potentially reflects the reduction in travel distance (De Vos 2020). Typological travel mobility derived from network science should be able to guide tourism researchers in elucidating the structural changes of tourism systems between pre- and post-COVID-19. Travel behaviors are heterogenous according to different seasonality and changes of situational factors. Accordingly, network motif analytics will facilitate DMOs' characterization of typological changes of travel flow, which is useful to develop destination planning post-COVID-19 (Reinhold, Laesser, and Beritelli 2020). Indeed, the method enables DMOs to catch variations in typological structures as well as numbers and order (directions) of places visited. This insight provides DMOs with the evolution of the city destination network across time, and guides strategic response to the change of environment.

While this research has made important contributions, it has several limitations. First, the data reflects travel behaviors in Seoul, South Korea. To assess the generalizability of the findings and suitability of network motif analytics, future researchers must assess travel mobility patterns in various contexts of destinations. Second, this research only analyzed movement data associated with the behavioral approach in understanding travel behaviors. Considering the mechanism of mobile sensor data operated by cellphone towers, one challenge would be to identify the exact locations of mobile users and their activities at these locations. As a result, the researchers emphasize the importance of data integration that combines data of both behavioral and psychological (perceptions) aspects. In this sense, future researchers who adopt a big data approach are strongly advised to obtain information about travelers' experiences, such as by surveys and/or interviews.

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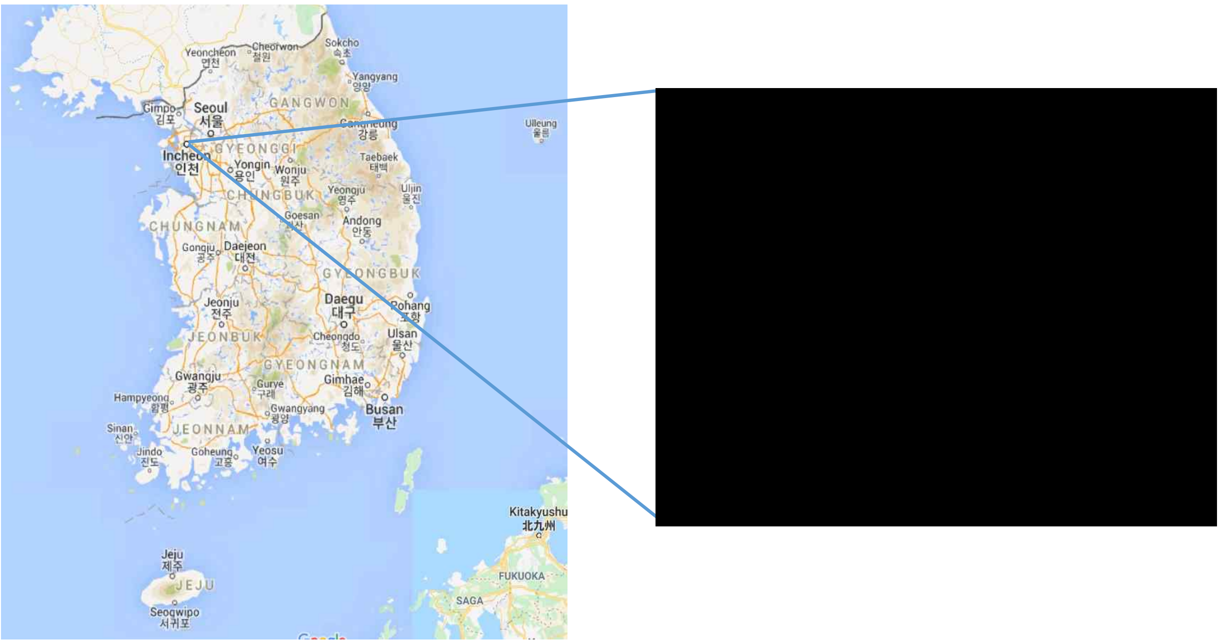
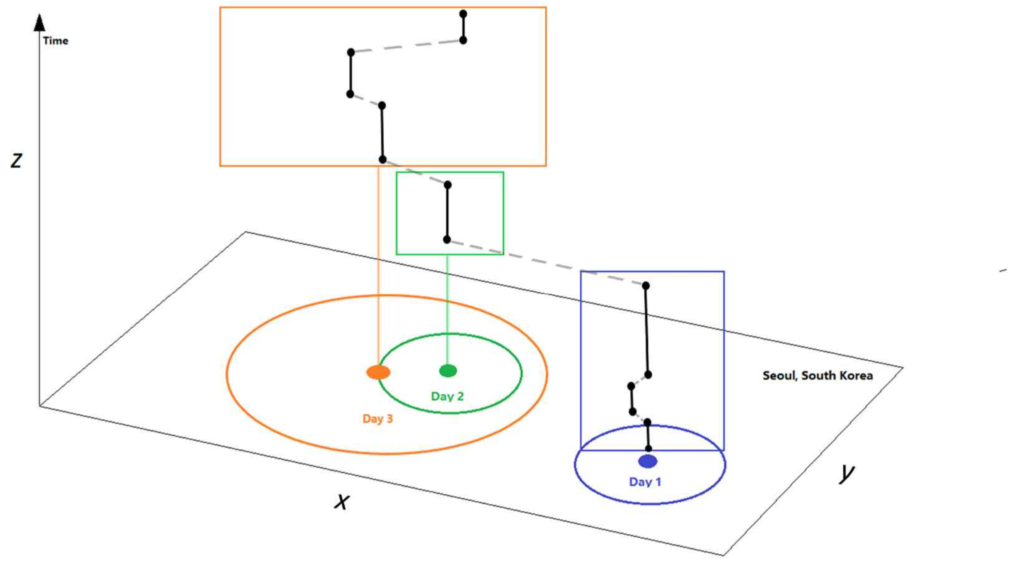


Figure 1. Study area - Seoul in South Korea.



Note: The X–Y plane represents geographical locations in Seoul and the Z-axis represents the timeline. A solid segment represents a cellphone tower record (nodes in the network motif) and the dashed line represents the movement period between two cellphone towers (edges the in the network motif).

Figure 2. An example of individual mobile trajectory from Day 1 to Day 3

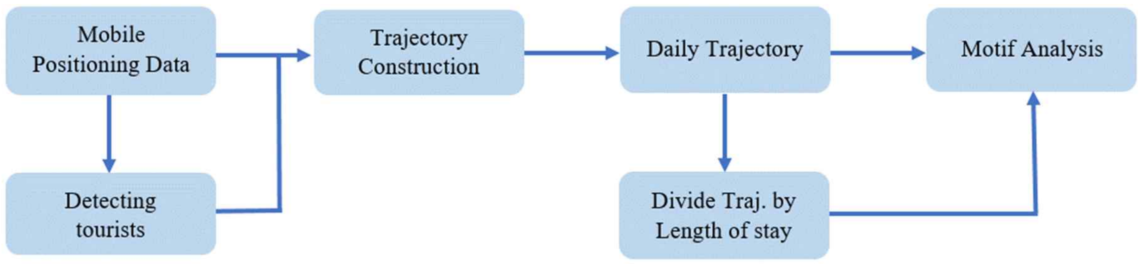
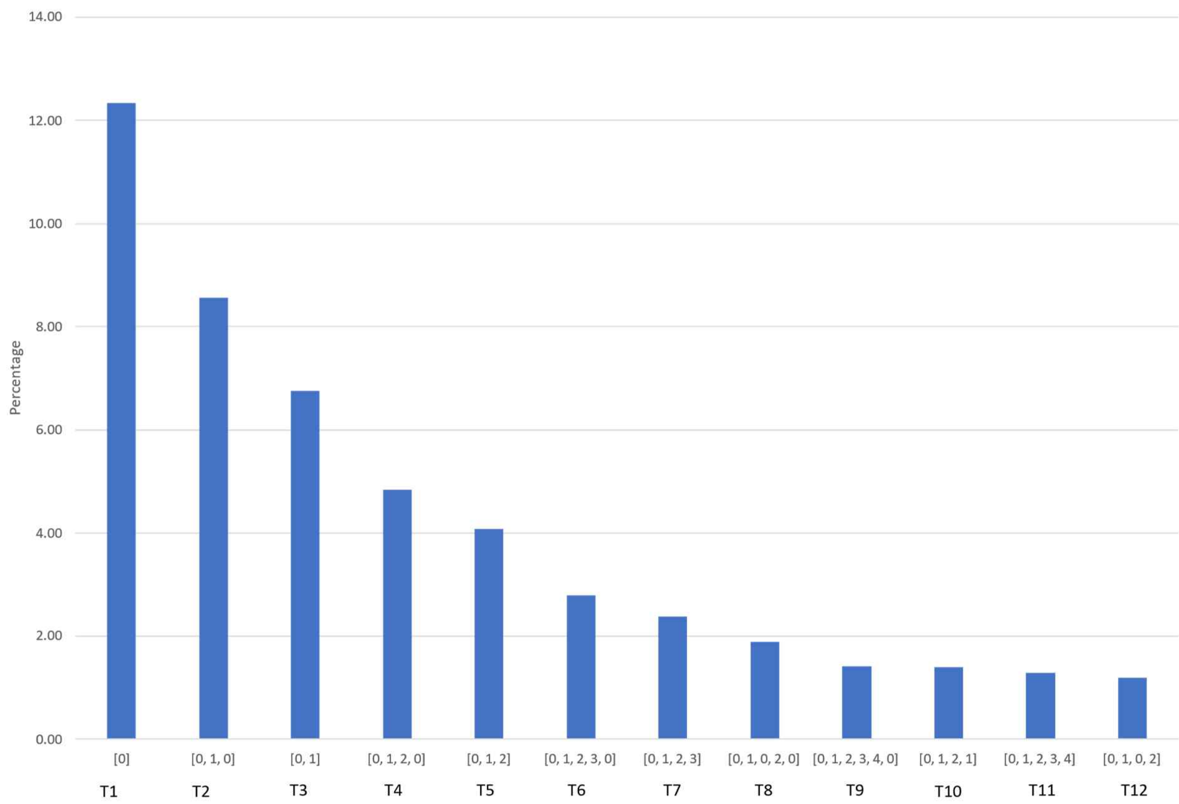


Figure 3. Analytical framework of the study



Note: T refers to types of travel movement patterns by network motif analytics

Figure 4. Results of top 12 types of travel flow patterns

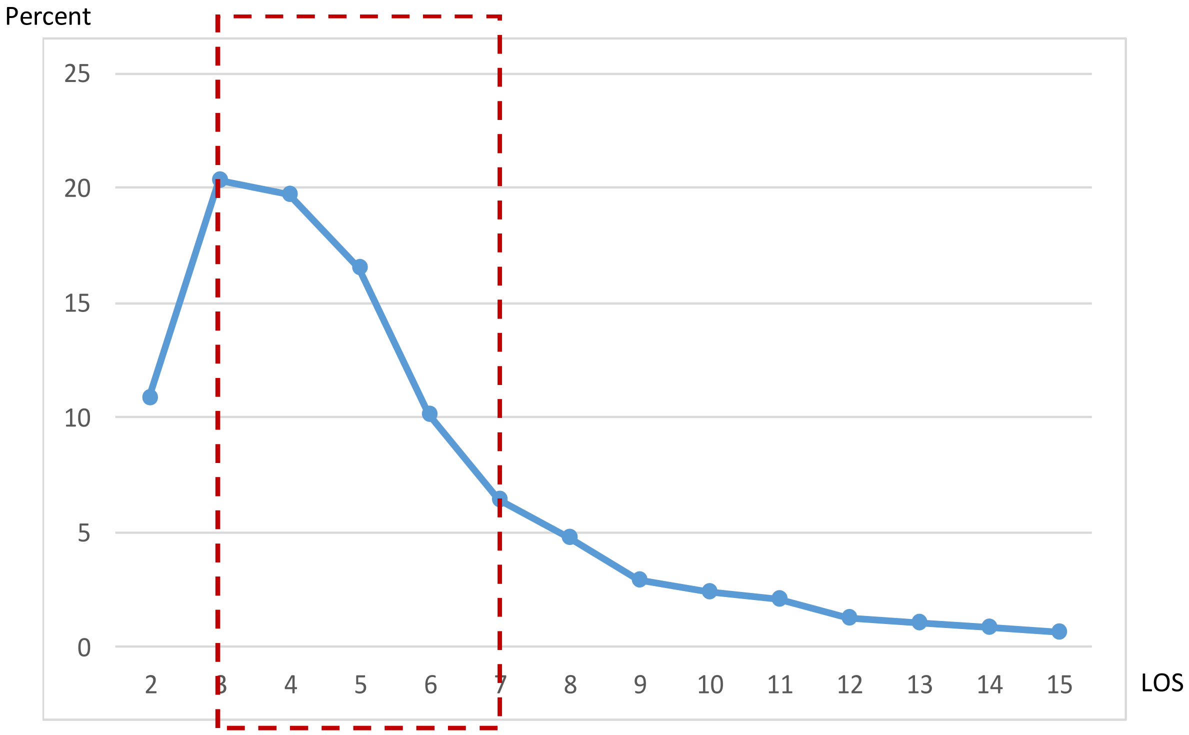


Figure 5. Distribution of length of stays in Seoul, South Korea

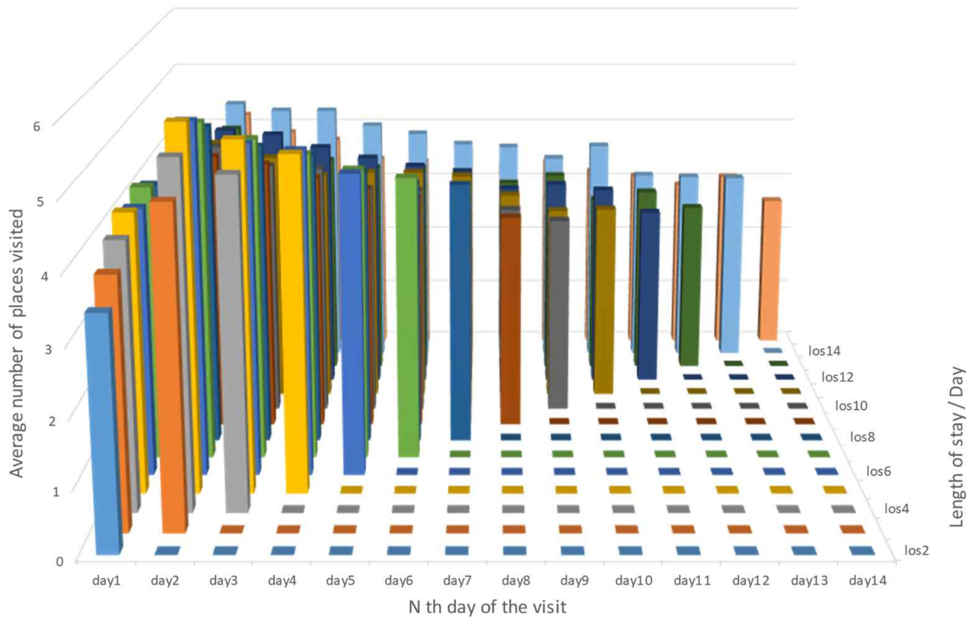


Figure 6. Average number of places visited according to LOS and Nth day of the visit

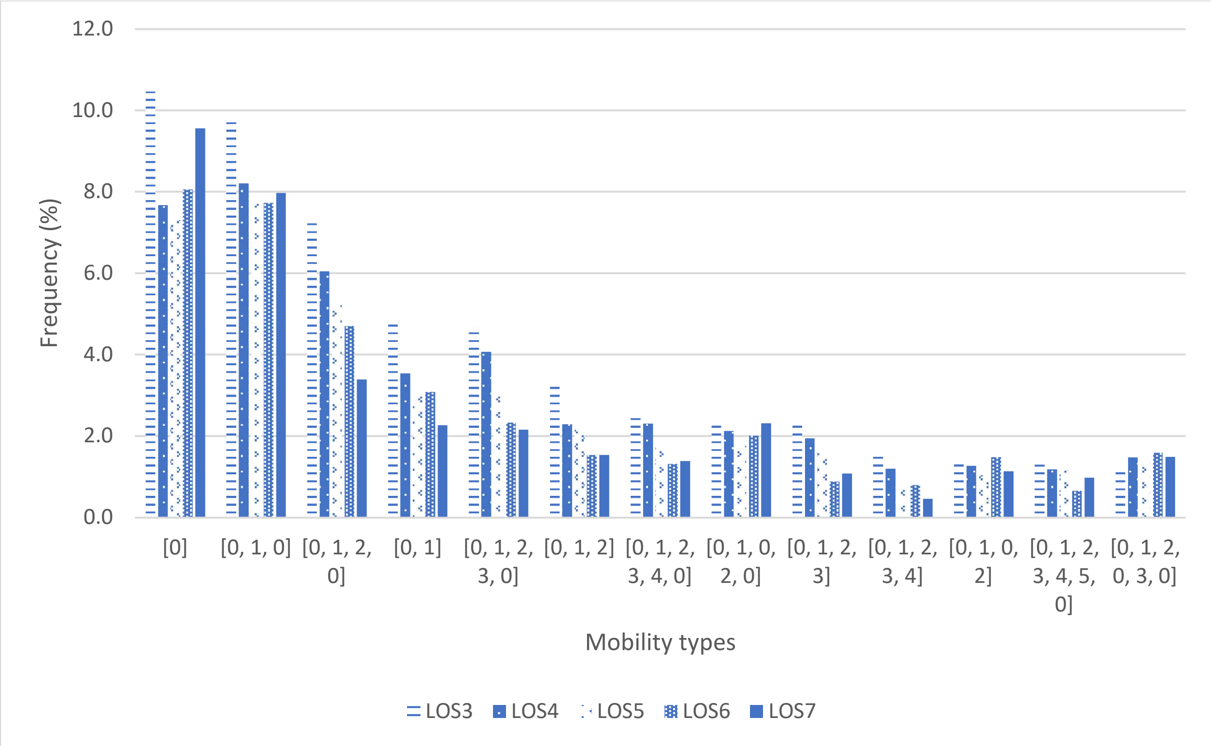
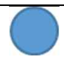
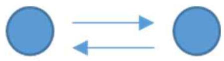
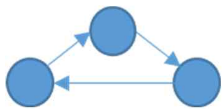
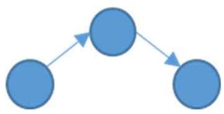
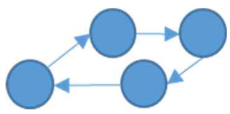
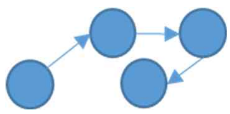
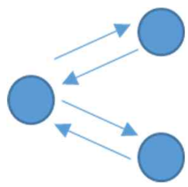
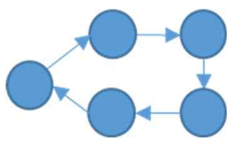
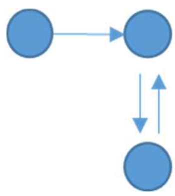


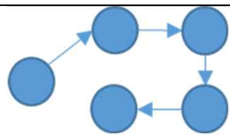
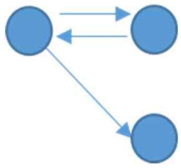
Figure 7. Frequency of second day flow patterns on five different length of stay groups (LOS = 3–7

Table 1. Example of individual mobile positioning dataset.

Date	User ID	Nationality	Start time	End time	Longitude	Latitude
20180801	R000001	***	00:14:00	08:57:00	126.***	37.***
20180801	R000001	***	09:47:00	10:41:00	127.***	37.***
…	…	…	…	…	…	…
20180815	R192302	***	11:35:00	12:29:00	127.***	38.***
20180815	R192302	***	21:53:00	23:35:00	128.***	38.***

Table 2. Summary of topological daily mobility patterns

Type (z-score)	Typology of Travel Patterns	Names of Movement Patterns
Type 1 (117.58)		No movement
Type 2 (81.53)		Cycle pattern
Type 3 (64.34)		Single distant stop
Type 4 (46.11)		Three-nodes cycle pattern (fully-connected triad)
Type 5 (38.84)		Three-nodes chain pattern
Type 6 (26.50)		Four-nodes cycle pattern
Type 7 (22.71)		Four-nodes chain pattern
Type 8 (18.04)		Centralized cycle pattern
Type 9 (13.49)		Five-nodes cycle pattern
Type 10 (13.32)		Uplinked mutual dyad chain

Type 11 (12.28)		Five-nodes chain pattern
Type 12 (11.38)		Downlinked mutual dyad chain