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Research paper

Identifying the spatial structure of the tourist attraction system in South Korea using GIS and network analysis: An application of anchor-point theory

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ABSTRACT

While social network analysis techniques have increasingly been applied in tourism research, limited effort has been devoted to attractions networks within a tourism destination. This study identified the spatial structure of the tourist attraction system in Seoul, South Korea. Based on anchor-point theory, social network analysis techniques with spatial statistics, such as local indicator of spatial autocorrelation (LISA), using Geographic Information Systems (GIS), were employed. Chinese Free Independent Tourist (FIT) data were used to compute the centrality measures from the 2015 International Visitor Survey. Results indicate that multiple anchor-points (i.e. attractions) can exist within a tourism destination. In addition, the spatial distribution patterns of the centralities were hierarchically structured and differentiated depending on the length of stay. These findings highlight the importance of examining the spatial structure of tourist attraction networks to better establish competitive tourism destination planning, development, and management strategies.

1. Introduction

According to Debbage (1991), since the spatial behavior of tourists is about exploring the wide geographic area of a destination during their trip, tourists' spatial behavior can be differentiated by tourists' typologies and travel preferences. For this reason, investigating tourists' movement patterns between/among multiple attractions could be essential to better understand tourists' spatial behavior (Caldeira & Kastenholz, 2017).

Tourists' spatial behavior within a destination is more complex than between/among destinations, since they tend to visit diverse attractions located within the destination during their trip (Lew & McKercher, 2006). Different tourist attractions are likely to have different degrees of significance, depending on the motivation of tourists (Leiper, 1990). Those differences may be hierarchically structured as a result of differences in the visitation frequency.

While defining 'tourist attraction' is difficult, Pearce (1991, p. 46) outlined "a tourist attraction is a named site with a specific human or natural feature which is the focus of visitor and management attention". Edelheim (2015) defines a tourist attraction as contribing to the narratives of place identity so that it relates to constructing the meaning of visitor experience. As a result, this study uses the definition of a tourist attraction by a hybrid of Pearce (1991) and Edelheim (2015).

Tourists' spatial behavior in urban destinations tends to comprise multi-attraction travel, involving a sequence of tourist attractions visited (Caldeira & Kastenholz, 2017). Because of the complex composition of tourist attractions visited during multi-attraction travel, tourism researchers have struggled to examine the nature of tourists' spatial behavior. However, since a tourist attraction can be counted as a node, and tourists' spatial movement between two attractions can be considered a link, social network analysis (SNA) has been widely used as a data-analysis technique by tourism researchers for analyzing the nature of the connections among attractions made by tourists' spatial movement (e.g. Asero, Gozzo, & Tomaselli, 2016; Hwang, Gretzel, & Fesenmaier, 2006; Jin, Cheng, & Xu, 2017; Lee & Kim, 2018; Leung et al., 2012; Liu, Huang, & Fu, 2017; Peng, Zhang, Liu, Lu, & Yang, 2016; Shih, 2006).

Regarding the significance of examining the nature of linkages between attractions, Lue, Crompton, & Fesenmaier (1993, p. 298) noted the following:

> … investigating the nature of linkages between destinations or attractions may help establish which types of tourism activities or resources should be located close to each other in order to maximize

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the financial return to both of them.

SNA has proven useful in previous tourist attraction network research. For example, Shih (2006) investigated the network characteristics of 16 drive tourism destinations in Nantou, Taiwan, by applying degree centrality, betweenness centrality, closeness centrality, and structural holes. The study demonstrated the appropriateness of network analysis techniques for examining the structural characteristics of tourism destinations. Similarly, Hwang et al. (2006) analyzed international tourists' trip patterns within the United States by applying network analysis methods such as centrality measures. They found that multi-city travel patterns differed with tourists' origins and varying levels of familiarity with the destination. Leung et al. (2012) visualized international tourists' movement patterns using the social network analysis software NetDraw, and found changes of movement patterns before, during and after the Beijing Olympic Games.

Recently, Asero et al. (2016) defined tourism networks using (social) network analysis methods. They revealed that destinations in Sicily can act as central or peripheral within a network, depending on tourist choice. A novel aspect of their approach, in comparison with previous studies, was that while Asero et al. (2016) also used degree, betweenness, and closeness centralities, they employed structural equivalence and CONvergence of iterated CORelation (CONCOR) procedures for clustering destinations. Peng et al. (2016) studied tourists' flows from a cross-provincial boundary perspective using SNA and Boundary Effect Analysis (BEA) methods, and Liu et al. (2017) examined the relationships among tourist attractions in a destination using the Quadratic Assignment Procedure (QAP) of SNA. Jin et al. (2017) analyzed tourists' movement networks against lengths of trip, and found temporal heterogeneity in the movements.

While the applicability of SNA methods has clearly been verified by a few empirical tourism studies, some suggestions made by previous studies for future research have not been sufficiently pursued. Specifically, Hwang et al. (2006) and Leung et al. (2012) suggested considering tourists' characteristics, such as socio-economic, demographic, and trip related behavior, when conducting SNA research. In a recent study, Liu et al., (2017, p. 140) also noted that "little attention has been given to the understanding of attractions network in the destination from tourist mobility perspective". As a result, since "attractions provide major symbols and images for the presentation of destinations to the public" (Pearce, 1991, p. 47), investigating which attractions are primary attractions and how the attractions are connected to each other are fundamental research questions to build effective and efficient tourism development, marketing, and management strategies.

From a theoretical perspective, anchor-point theory developed by Golledge (1978) may provide new implications for better understanding the spatial structure of tourist attractions, since the theory was developed to study "hierarchical ordering of locations, paths, and areas within the general spatial environment" (Golledge & Stimson, 1997, p. 167). As Jin et al. (2017) iterated, while the distribution and order of attractions visited by tourists are likely to vary depending on tourists' time availability during a trip, due to such variables as length of travel, little research has examined if attraction networks can be differentiated by length of travel.

To fill the gaps in the current literature, this study has two purposes, 1) to identify the nature of tourist attraction networks in light of tourists' characteristics such as the length of stay; and 2) to demonstrate the application of anchor-point theory to tourist attraction research.

2. Literature review

2.1. Anchor-point theory

The anchor-point theory of spatial cognition pioneered by Golledge (1978) addresses hierarchical linking of places (Golledge & Stimson, 1997), which is conceptually similar to landmarks, spatial hierarchies, and nodes in semantic net theories developed in geography, psychology, and cognitive science (Couclelis, Golledge, Gale, & Tobler, 1987). However, the concepts of anchor-point differ from those of the other theories in explaining the spatial cognition process.

The notion of the anchor in anchor-point theory has a distinctive nature comparable to the notion of landmark, which was popularized by Lynch (1960) 'The Images of the City,' which argued that "landmarks tend to be collectively as well as individually experienced as such, whereas anchors refer to *individual* cognitive maps" (Couclelis et al., 1987, p. 102). In analogy to the concept of spatial hierarchy, Couclelis et al., (1987, p. 103) proposed a cognitive map of the US, anchored by the location of important cities, e.g. "New York, Chicago, San Francisco, Denver or Los Angeles, by linear elements such as the Mississippi River or the Rockies, and by areal elements such as the Great Lakes or the South".

While the tools of both anchor-point and semantic net analyses include a hierarchical network of nodes (i.e. places), linked via a process of spreading activation, Couclelis et al. (1987) pointed out substantial differences between the two concepts. An anchor-point network is based on a configuration of points and lines in actual Euclidean space, while a semantic net represents "a conceptual structure with no direct analog in the observable world" (Couclelis et al., 1987, p. 103). Couclelis et al., (1987, pp. 103–104) further noted that

> … semantic nets allow for considerable heterogeneity in the type of concepts represented … whereas anchor-point hierarchies consist only of places, and links between places (the latter may correspond to real routes between places or may be more abstract, relational links)

Finally, semantic nets are meant to represent declarative knowledge only, while anchor-point configurations obscure the distinction between the declarative and the procedural/functional and relational aspects of spatial knowledge (Couclelis et al., 1987). As a result, anchor-point theory may reveal new insights to interpret tourism spaces.

Tourism researchers have paid little attention to the potential of anchor-point theory for understanding how tourists travel in unfamiliar environments (Walmsley & Jenkins, 1992). The anchor-points refer to primary attractions. Thus, as anchor-point theory highlights the relative significance of each attraction, the theory can illuminate hierarchical ordering of attractions (Golledge & Stimson, 1997). Identifying anchor-point attractions (i.e. primary attractions) within a destination is crucial to increasing the competitiveness of a destination.

Accordingly, this study is the first to apply the anchor-point theory to find anchor-point attractions within a destination by investigating the connections between attractions. Fig. 1 visualizes anchor-point theory. For example, of 15 tourist attractions, A1 is the anchor-point in Fig. 1, since tourist attractions A2 to A15 are hierarchically ordered under A1. For example, if a tourist visited multiple attractions during his/her trip, a few attractions may be must-see attractions, while other attractions may be visited depending on tourists' motivations, preferences, etc. These travel patterns may be best explained by anchor-point theory.

2.2. Tourist attraction research from a spatial perspective

Lew (1987) classified tourist attraction studies on a basis of three perspectives: ideographic listing, organization, and tourist cognition of attractions. Leiper (1990) proposed a model of tourist attraction systems consisting of tourist, nucleus (i.e. attraction), and marker (i.e. information). He suggested that tourist attractions can be hierarchically classified into primary, secondary, and tertiary categories. Shoval and Raveh (2004) categorized tourist attractions into four distinct groups: (1) main tourist sights, (2) tourist attractions in the '*Holy Basin*,' (3) tourist attractions in the new part of the city, and (4) shopping and entertainment areas. They found a tendency for spatial concentration

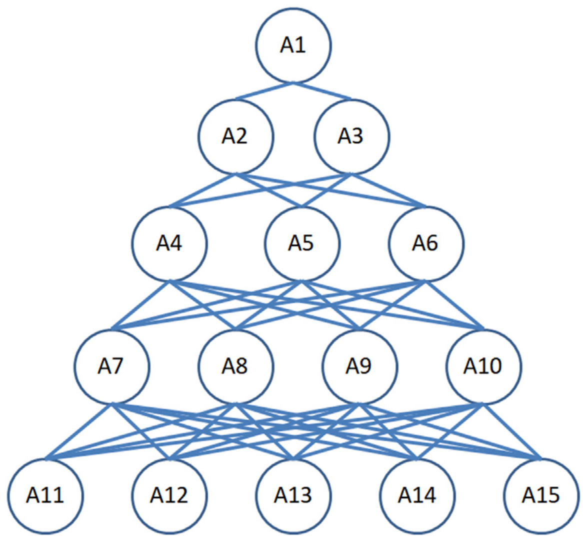

Fig. 1. Anchor-point theory.

among sights belonging to the same group. Length of stay and number of previous visits were important in differentiating among tourist attractions. Botti, Peypoch, and Solonandrasana (2008) elaborated a tourist attraction theory by involving means of time.

Weidenfeld, Butler, and Williams (2010) sought to link notions of clustering and compatibility with the importance of spatial scale, such as regional versus local relationships. They found that "spatial density and proximity between attractions are positively related to their collective compatibility at the regional scale, and compatibility between individual attractions at the local scale" (Weidenfeld et al., 2010, p. 14). Jin et al. (2017) confirmed the power law of distance decay in tourists' intra-urban movements, indicating that tourist' movements are less sensitive to distance than inter-city and the daily human movements, and thus revealed the roles of time in perceiving, ranking, and visiting primary attractions.

More recently, tourism researchers have become interested in investigating tourists' spatial behavior capitalizing on advances in techniques and methods that were not part of traditional tools for tourism research, such as GIS and GPS for movement tracking (e.g. Lau & McKercher, 2006; McKercher & Lau, 2008; McKercher, Shoval, Ng, & Birenboim, 2012; Zoltan & McKercher, 2015) and SNA for structure analysis of tourist attractions (e.g. Asero et al., 2016; D'Agata, Gozzo, & Tomaselli, 2013; Hwang et al., 2006; Jin et al., 2017; Lee, Choi, Yoo, & Oh, 2013; Leung et al., 2012; Liu et al., 2017; Peng et al., 2016; Scott, Cooper, & Baggio, 2008; Shih, 2006; Stienmetz & Fesenmaier, 2015).

Fig. 2 shows two lines of research emphasis, the first focusing on tourists' movement patterns and types within a given space and the second focusing on structures and characteristics of attractions. Unlike most tourist attraction studies using traditional statistical methods such as regression and structural equation modeling, the GIS, GPS, and SNA approaches adopted in previous studies have found inter- or intra-destination movement paths and patterns of tourists.

2.3. Length of stay and spatial behavior of tourists

Debbage (1991) found tourists' socio-economic characteristics (i.e. income, education, age, and occupation), type of travel arrangement (i.e. packaged tour vs. independent travelers), familiarity level (i.e. first-time vs. repeat travelers), and party size to be not significant in determining their spatial behavior. He reported that the major determinants of the spatial behavior of tourists within a destination were the temporal constraints and the spatial structure of the destination environment, such as length of stay, mobility levels, origin of the tourist, and place of stay. Oppermann (1994) revealed that tourists' spatial behavior is more dispersed from the main gateways and major tourist attractions as their length of stay increases. Furthering this finding, examining benefit sought market segments among French leisure travelers visiting Canada, Lee, Morrison, and O'Leary (2006) found out length of stay is a key factor influencing destination expenditure and activity patterns. From these empirical findings, we can infer that length of stay is closely related to the functional hierarchy of places in a destination as Oppermann (1994) suggested. Within the framework of anchor point theory, this study aims at the systematical analysis of the network structure, defined by length of stay, and the functional roles each attraction plays within the structure.

Wu and Carson (2008) showed different dispersal behavior between domestic and international tourists; length of stay had less impact on the dispersal of domestic tourists, while international tourists concentrated at major cities in the beginning of the tour and then gradually dispersed to regional destinations. Recently, Kang (2016) revealed that length of stay can be recognized as a constraint associated with the spatial patterns of travels. The only study examining the relationship

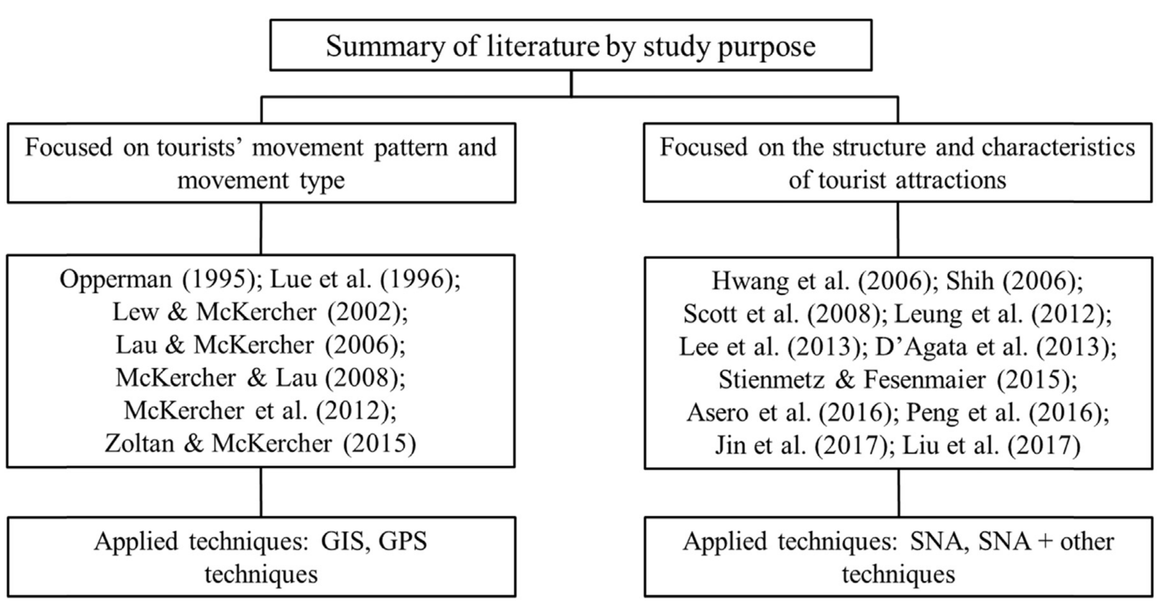

Fig. 2. A summary of literature by study purpose.

between length of stay and spatial behavior of tourists is a recent one conducted by Jin et al. (2017). They found temporal heterogeneity of tourists' movements. For example, there were differences between short-period and long-term trips in attraction visits; short-period tourists tended to visit primary attractions, while for long-term tourists, the attraction hierarchy of their movement was weakened, since long-term tourists tended to visit more attractions within a shorter distance.

Previous studies have confirmed the influence of length of stay on tourists' multi-destination travel (Caldeira & Kastenholz, 2017). Leung et al. (2012) suggested that length of stay can affect tourists' travel activities, and thus proposed further research on this question. As of today, only scanty research can be found in existing literature examining that question; one of the few studies is Jin et al. (2017), which examined how the length of stay factor can affect tourists' movement. Noting a significant gap regarding this research question, the study also emphasized the need for exploring "the temporal heterogeneity of tourism mobility in a non-Western context" (Jin et al., 2017, p. 11). Accordingly, findings of this study may reveal evidence relevant to the suggestion of Jin et al. (2017).

2.4. The use of geographic information systems (GIS) for visualizing spatial behavior of tourists

While tourists' spatial behavior (i.e. movement patterns) within a destination is quite complex, a precedent has been set for using GIS to visualize patterns within such behavior. For example, McKercher and Lau (2008) used GIS to identify a total of 78 discrete movement patterns within an urban destination (i.e. Hong Kong) based on a sample of 250 tourists. McKercher et al. (2012) compared differences in spatial behavior between first-time and repeat visitors and found that first-time visitors tended to travel more widely throughout the destination than repeaters. In a further example, Zoltan and McKercher (2015) employed GIS to analyze intra-destination movements and activity participation of tourists through destination card consumption in the Canton of Ticino, Switzerland and found spatial structure of a tourism destination to influence tourists' spatial behavior.

2.5. Research questions

Based on literature review, this study suggests two research questions as follows:

RQ1: There are differences in the distribution patterns of normalized degree centralities among the length of stay networks.
RQ2: There are differences in the distribution patterns of normalized eigenvector centralities among the length of stay networks.

3. Methods

3.1. Study region

The region selected for this study is Seoul, the capital city of South Korea (see Fig. 3) and a frequent tourist destination. The results of the '2015 International Visitor Survey' (Ministry of Culture, Sports & Tourism, 2016) indicated that 78.7% of the leisure travelers to South Korea who participated in the survey had visited Seoul as a tourism destination. They tended to visit attractions located in the center of Seoul: 77.1% of them had visited Myeong-dong, 60.3% had visited the Dongdaemun Market, and 44.3% had visited the Chosun Dynasty Palaces (see Table 1).

3.2. Sources of data

The data considered for this study were those of the above-mentioned '2015 International Visitor Survey,' collected by the Ministry of Culture, Sports and Tourism in South Korea.

Foreign tourists departing South Korea after visiting were intercepted and asked to participate in a self-administered survey about their visit to South Korea. The target population was 11,562,192 persons, excepting overseas South Koreans and crew members, and the sample size was 12,900 persons, meaning at least 1000 responses per month were collected. Only tourists aged 15 and over who had stayed more than one day but less than one year were surveyed. Travelers in South Korea for transfer, airplane captains, crew members, and soldiers not visiting for a tour were excluded. The survey sites were counter lobbies in Incheon, Kimpo, Kim Hae, and Jeju international airports and Incheon and Busan international harbors.

Of the international visitors to South Korea in 2015, 47.3% were Chinese tourists, and 67.9% of them were free independent tourists (FITs) (Ministry of Culture, Sports, and Tourism, 2016). Thus, examining Chinese FITs' tourism behavior is a task crucial for South Korea's tourism growth and development. Accordingly, the current study used a subset of the data consisting of responses from Chinese FITs who had visited more than three tourist attractions located in Seoul. In addition, when a tourist's length of stay was more than 90 days, the data were excluded. As a result, a total of 825 respondents' data constituted the subject of the analysis.

3.3. Measurement

Length of stay was measured by the question 'How long did you stay in Korea?' Respondents answered '() Day(s) / () Night(s).' The average length of stay was 6.1 nights, meaning mean = 6.1, mode = 5, median = 5. Based on these statistics, the numeric responses were collapsed into three categories: below average or short stay (more than one night, but no more than four nights), around average or medium stay (more than five nights, but no more than seven nights), and above-average or long stay (more than eight nights, but no more than 90 nights) (see Debbage, 1991).

Destinations visited by the Chinese FITs were obtained by the multiple choice item, 'Indicate all locations you visited while traveling in Korea this time.' Respondents chose or listed tourist attractions they visited, as shown in Table 2.

These attractions constitute a mixture of free and for-charge admission sites. It must be noted that the data did not contain directional information, i.e. the order of visitation of the destinations was not elicited. In cases where this information is lacking, computer programs (e.g. UCINET) for SNA may calculate betweenness and closeness centralities, but those centralities may not be presumed to be meaningful. Thus, for this study, only degree and eigenvector centralities were computed.

3.4. Analysis

3.4.1. Social Network Analysis (SNA)

Based on the nature of the data, specifically the lack of directional data, the most reliable measures for SNA are the degree and eigenvector centralities. Because this study compares the centralities among three different networks, normalized centrality measures developed by Freeman (1978) were employed. Degree, betweenness, and closeness centralities can be used to compare actors such as attractions in the same network (Prell, 2012), while normalized centrality measures can be applied to compare the centralities of attractions between/among networks. Therefore, normalized degree and eigenvector centralities were computed by UCINET 6 for Windows (Borgatti, Everett, & Freeman, 2002).

Three symmetrical matrices of binary values (i.e. either 1 s or 0 s) were prepared for the length of stay networks (i.e. short, medium, and long stay networks). A cut-off value for determining the binary values was 2, following Shih (2006). Thus, when the frequency of visitation between two attractions was more than 2, it was re-coded as 1. Otherwise, it was re-coded as 0.

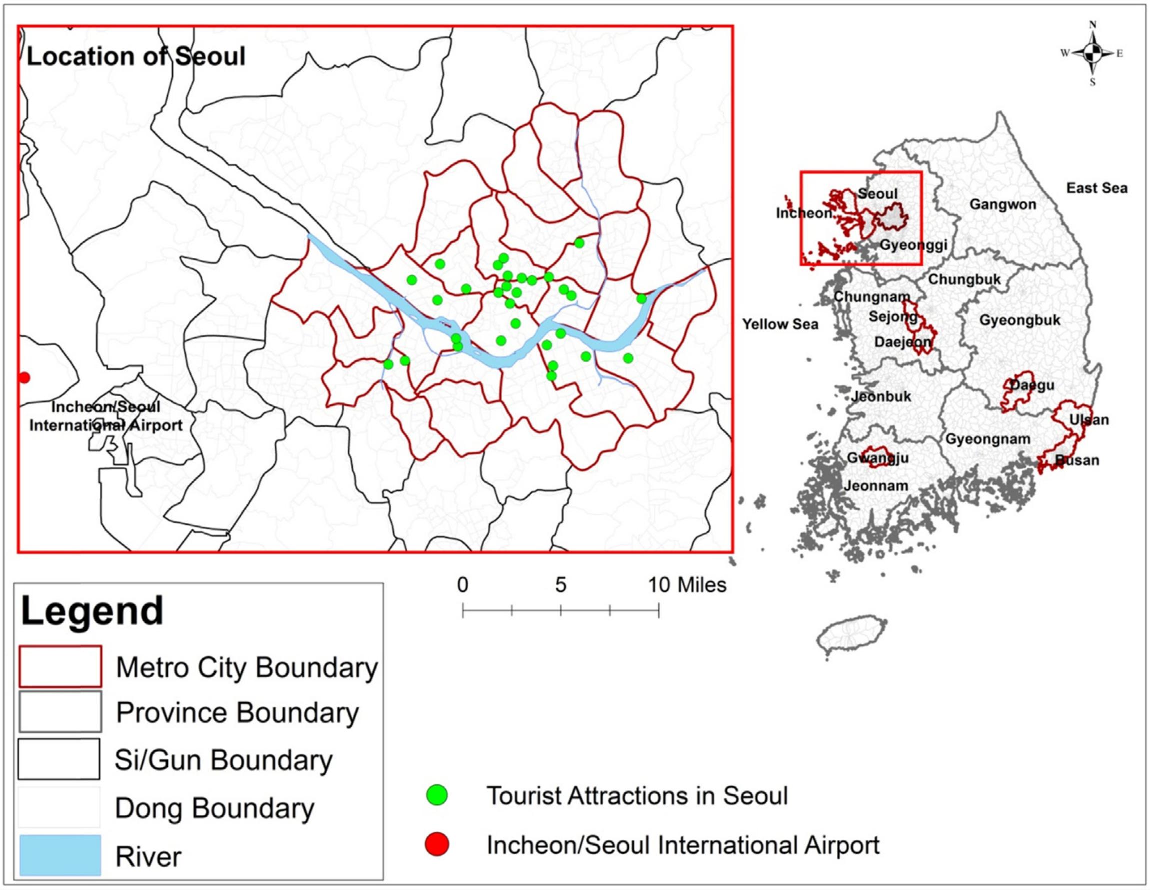

Fig. 3. Location of Seoul, South Korea. Note: This map is an original work of the authors.

Table 1
Destination distribution (%) visited by international tourists to Seoul, 2015. Source: 2015 International Visitor Survey report (Ministry of Culture, Sports & Tourism, 2016).

Rank	Destination	Percentage
1	Myeong-dong	77.1%
2	Dongdaemun Market	60.3%
3	Chosun Dynasty Palaces	44.3%
4	Namsan/N Seoul Tower	40.7%
5	Sinchon/Hongik Univ.	29.1%
6	Namdaemun Market	29.0%
7	Museums (Memorial Halls)	26.7%
8	Insa-dong	25.8%
9	Jamsil (Lotte World)	23.4%
10	Gangnam station	23.1%

Note: Multiple responses were allowed.

Table 2
Tourist attractions.

Tourist attractions
(1) Palaces (2) Museums (Memorial Halls) (3) Insa-dong (4) Namsan/N Seoul Tower (5) Myeong-dong (6) Namdaemun Market (7) COEX (8) Dongdaemun Market (9) Itaewon (10) Jamsil (Lotte World) (11) Yeouido/63 Building (12) Hangang River/Ferry (13) Cheonggyecheon (14) Sinchon/Hongik University. (15) DMC/World Cup Stadium (16) Hanok village(Namsan) (17) Bukchon/ Samcheong-dong (18) Cheongdam-dong/Apgujeong-dong (19) Garosu-gil street (20) Gangnam station (21) Other Locations in Seoul Not Listed Above:

This study identified that short stay tourist, medium stay tourist, and long stay tourists visited twenty-nine tourist attractions in Seoul using the 2015 International Visitor Survey data. This study utilized 29 tourist attractions to construct length of stay networks. In addition, of the 825 responses, short-stay, medium-stay, and long-stay networks were constructed using 279, 406, and 140 respondents' data, respectively.

For a short-stay network, a matrix of 279 respondents by 29 attractions was prepared. The matrix was transformed to a matrix of 29 attractions by 29 attractions, which was thus considered a short-stay network. For a medium-stay network, a matrix of 406 respondents by 29 attractions was transformed to one of 29 attractions by 29 attractions, which was finalized as the medium-stay network. For a long-stay network, a matrix of 140 respondents by 29 attractions was transformed to one of 29 attractions by 29 attractions to be used for the long-stay network.

3.4.2. *Normalized degree centrality*

Normalized degree centrality is a degree centrality score converted into proportions (Freeman, 1978). Using this conversion, a researcher is able to compare the centrality of actors such as attractions from one network to the next (Prell, 2012).

Degree centrality is the number of immediate connections an attraction has in a network. Since degree centrality ignores both the direction and value of the tie, degree centrality can be used to measure an attraction's level of involvement, prestige, or dependence in the network (Prell, 2012). An attraction with high degree centrality can be considered a major tourist attraction for spreading tourists in that particular network. The degree centrality can be formulated as follows, though UCINET calculates the degree centralities of each attraction:

Degree centrality, for attraction *i*:

Table 3
Characteristics of respondents.

Short stay (n = 279)		Medium stay (n = 406)		Long stay (n = 140)	
Characteristics	Frequency (%)	Characteristics	Frequency (%)	Characteristics	Frequency (%)
Gender		Gender		Gender	
Male	99 (35.5)	Male	131 (32.3)	Male	49 (35.0)
Female	180 (64.5)	Female	275 (67.7)	Female	91 (65.0)
Total	279 (100.0)	Total	406 (100.0)	Total	140 (100.0)
Education		Education		Education	
Elementary school / high school	20 (7.2)	Elementary school / high school	47 (11.6)	Elementary school High school	16 (11.4)
College/University graduate	215 (77.1)	College/university graduate	308 (75.9)	College/University graduate	109 (77.9)
Post-Graduate	30 (10.8)	Post-graduate	40 (9.9)	Post-Graduate	10 (7.1)
Other	11 (3.9)	Other	10 (2.5)	Other	4 (2.9)
NA	3 (1.1)	NA	1 (0.2)	NA	1 (0.7)
Total	279 (100.0)	Total	406 (100.0)	Total	140 (100.0)
Occupation		Occupation		Occupation	
Government or armed forces	12 (4.3)	Government or armed forces	16 (3.9)	Government or Armed forces	3 (2.1)
Business executive or manager	22 (7.9)	Business executive or manager	25 (6.2)	Business Executive or Manager	7 (5.0)
Clerical worker or technician	61 (21.9)	Clerical worker or Ttechnician	98 (24.1)	Clerical worker or Technician	20 (14.3)
Sales or service worker	38 (13.6)	Sales or service worker	39 (9.6)	Sales or Service worker	7 (5.0)
Specialized job (professor, doctor, lawyer, etc.)	22 (7.9)	Specialized job (professor, doctor, lawyer, etc.)	29 (7.1)	Specialized Job (Professor, Doctor, Lawyer, etc.)	7 (5.0)
Factory worker	1 (0.4)	Factory worker	5 (1.2)	Factory worker	2 (1.4)
Self-employed	75 (26.9)	Self-employed	71 (17.5)	Self-Employed	24 (17.1)
Student	21 (7.5)	Student	55 (13.5)	Student	43 (30.7)
Home worker	8 (2.9)	Home worker	17 (4.2)	Home worker	6 (4.3)
Retired	2 (0.7)	Retired	1 (0.2)	Retired	1 (0.7)
Unemployed	1 (0.4)	Unemployed	16 (3.9)	Unemployed	8 (5.7)
Other	15 (5.4)	Other	32 (7.9)	Other	12 (8.6)
NA	1 (0.4)	NA	2 (0.5)	NA	–
Total	279 (100.0)	Total	406 (100.0)	Total	140 (100.0)
Age		Age		Age	
15–20	10 (3.6)	15–20	20 (4.9)	15–20	18 (12.9)
21–30	136 (48.7)	21–30	245 (60.3)	21–30	80 (57.1)
31–40	111 (39.8)	31–40	104 (25.6)	31–40	28 (20.0)
41–50	16 (5.7)	41–50	26 (6.4)	41–50	10 (7.1)
51–60	5 (1.8)	51–60	10 (2.5)	51–60	3 (2.1)
60 <	1 (0.4)	60 <	–	60 <	1 (0.7)
NA	–	NA	1	NA	–
Total	279 (100.0)	Total	406 (100.0)	Total	140 (100.0)

NA = not available.

$$C_D(i) = \sum_{j=1}^{n} x_{ij} = \sum_{i=1}^{n} x_{ji}$$

Where, x_{ji} = the value of the tie from attraction i to attraction j (the value being either 0 or 1). It is the sum of all ties (i.e., connections) between attractions. n = the number of attractions in the network.

Normalized degree centrality:

$$C'_D(i) = \frac{C_D(i)}{g-1}$$

Where, $C'_D(i)$=normalized degree centrality of attraction i, $C_D(i)$= degree centrality of attraction i, g = the number of attractions

3.4.3. Normalized eigenvector centrality

The normalized eigenvector centrality is used when a data set has no directional information or is undirected, meaning symmetric (Prell, 2012). The normalized eigenvector centrality is the normalization of the sum of an attraction's connection to other attractions, weighted by their degree centrality (Prell, 2012). Thus, since a major advantage of the normalized eigenvector centrality is its usefulness in considering immediately adjacent attractions to a focal attraction, "eigenvector centrality can be seen as a more refined version of degree centrality" (Prell, 2012, p. 101). In other words, the normalized eigenvector centrality considers how many connections an attraction has. More importantly, the normalized eigenvector centrality score reflects attractions not only directly connected to, but also indirectly connected to, other attractions. Thus, this study computed the normalized eigenvector centrality scores along with normalized degree centrality scores.

3.4.4. Visualization with centralities using GIS

While SNA focuses on the actors, such as attractions themselves, and the relationship between and among them (Leung et al., 2012), GIS can visually represent the nature of those relationships (i.e. centralities) with the locational information of attractions (see Lee et al., 2013). Using this technique, this study maps not only centralities but also distributional patterns of the centralities. ArcGIS 10.4.1 was employed to visualize those centralities on maps.

3.4.5. Local Indicators of spatial association

While visualization with centralities using GIS can show the spatial patterns of the centralities, visualization technique cannot reference statistical significance of the spatial patterns. To reveal the significant associations between the centralities, local indicators of spatial association (LISA) analysis was employed. As one of the exploratory spatial data analysis techniques, LISA can identify the location and type of spatial cluster in a data set based on the concept of spatial dependence (Kang, Kim, & Nicholls, 2014). In this study, LISA can be calculated as follows:

$$I_i = \frac{(x_i - \mu)}{m_2} \sum_i w_{ij}(x_j - \mu), \quad m_2 = \sum_i (x_i - \mu)^2/N$$

where I_i is the local Moran's I statistic at tourist attraction i; w_{ij} is the matrix of weights such that $w_{ij}=1$ if tourist attraction i and tourist attraction j are adjacent; otherwise, $w_{ij}=0$, x_i is the attribute value of a specific variable at tourist attraction i, x_j is the attribute value of a specific variable at tourist attraction j, μ is the average attribute value of a specific variable, and N is the total number of tourist attractions.

Results of LISA analysis can be presented in five categories: (1) High-High (HH): spatial clusters of tourist attractions with high centralities, indicating hot spots; (2) High-Low (HL): tourist attractions with high centralities adjacent to tourist attractions with low centralities, indicating spatial outliers; (3) Low-High (LH): tourist attractions with low centralities adjacent to tourist attractions with high centralities; (4) Low-Low (LL): spatial clusters of tourist attractions with low centralities, indicating cold spots; and (5) Not Significant: no clustering between tourist attractions (Jang & Kim, 2018; Jang, Kim, & Zedtwitz, 2017). ArcGIS 10.4.1 was also applied for the LISA analyses.

4. Results

4.1. Respondent characteristics

Basic characteristics of the sample such as the number of males and females, occupation, and education level are summarized in Table 3. Across the three groups (i.e. short stay, medium stay, and long stay), the proportion of female respondents were higher than male. Most respondents' educational levels were college/university graduate, and their age was 21–30 years old.

However, there were differences in occupation among the three groups. Most short-stay respondents were self-employed, while medium-stay respondents tended to be clerical workers or technicians. Long-stay respondents were mostly students.

4.2. Frequency distribution of major 10 attractions in Seoul, South Korea, by length of stay

Table 4 shows the frequency distribution of the major 10 tourist attractions among 29 tourist attractions located in Seoul, South Korea, by the length of stay. Of the ten attractions, those visited by more than 60% of the respondents were Myeong-dong (short stay = 25.9%, medium stay = 22.3%, long stay = 22.5%), Dongdaemun Market (20.0%, 17.6%, 17.3%), Namsan/N Seoul Tower (10.5%, 12.6%, 11.8%), and Sinchon/Hongik University. (9.3%, 10.6%, 9.8%).

Of the 279 short stay respondents, 4.3% visited Insa-dong, which was thus ranked tenth, while of the 140 long stay respondents 7.1% visited Insa-dong, thus ranked fifth. Interestingly, only medium-stay and long- stay respondents visited Garosu-gil Street (4.2%) and Hangang River/Ferry (6.6%), respectively.

4.3. Descriptive characteristics of length of stay networks

Table 5 shows descriptive characteristics of length-of-stay networks

Table 5
Descriptive characteristics of the networks of length of stay.

	Short stay	Medium stay	Long stay
Number of nodes	29	29	29
Number of ties	286	350	294
Density	0.352	0.431	0.362
Degree centralization index	35.05%	26.59%	30.16%
Eigenvector centralization index	20.97%	14.98%	19.65%

with the number of nodes, number of ties, density, degree centralization index, and eigenvector centralization index. The number of nodes is the number of attractions. The number of ties is the number of connections between two attractions. As density is the total number of ties divided by the total number of possible ties, higher network density corresponds to stronger connection between attractions (Borgatti et al., 2002; Leung et al., 2012).

The densities of the short-stay, medium-stay, and long-stay networks were 0.352, 0.431, and 0.362, respectively. Thus, the medium-stay network was more centralized than the short-stay and long-stay networks. This finding shows that medium-stay tourists cohesively visited multiple tourist attractions, while short-stay tourists' attraction visit patterns tended to be hierarchical.

Degree and eigenvector centralization indices show the extent of concentration in the whole network. When considering only direct connections between attractions, short stay (35.05%) was the most concentrated network (long stay = 30.16%, medium stay = 26.59%). The eigenvector centralization index, counting direct and indirect connections between attractions, revealed the same patterns as the degree centralization index – short stay (20.97%) was the most concentrated network. The centralization indices of both degree and eigenvector indicate that the power of individual attractions varies rather substantially. More specific information regarding each attraction's extent of centralization in a network was investigated using degree and eigenvector centrality measures, and the results are provided in Tables 6, 7.

4.4. Comparing tourist attractions in length of stay networks

Table 6 indicates that for all networks (i.e. short-, medium-, and long-stay networks), Myeong-dong ranked first, at 67.857% for short- and medium-stay and 64.286% for long. Thus, the evidence suggests that Myeong-dong is a prestige attraction in those networks located in Seoul and can be depended on to attract tourists.

However, another interesting finding was that some attractions Dongdaemun Market, Namsan/N Seoul Tower, and Sinchon/Hongik University also ranked first for both medium-stay and long-stay

Table 4
Frequency distribution of major ten attractions in Seoul, South Korea, by length of stay.

Short stay (n = 279)				Medium stay (n = 406)				Long stay (n = 140)			
Rank	Attractions	Frequency	%	Rank	Attractions	Frequency	%	Rank	Attractions	Frequency	%
1	Myeong-dong	261	25.9	1	Myeong-dong	390	22.3	1	Myeong-dong	133	22.5
2	Dongdaemun Market	201	20.0	2	Dongdaemun Market	308	17.6	2	Dongdaemun Market	102	17.3
3	Namsan/N Seoul Tower	106	10.5	3	Namsan/N Seoul Tower	220	12.6	3	Namsan/N Seoul Tower	70	11.8
4	Sinchon/Hongik Univ.	94	9.3	4	Sinchon/Hongik Univ.	186	10.6	4	Sinchon/Hongik Univ.	58	9.8
5	Palaces	76	7.5	5	Palaces	133	7.6	5	Insa-dong	42	7.1
6	Namdaemun Market	72	7.1	6	Insa-dong	122	7.0	6	Palaces	40	6.8
7	Jamsil (Lotte World)	61	6.1	7	Jamsil (Lotte World)	116	6.6	7	Namdaemun Market	40	6.8
8	Cheonggyecheon	48	4.8	8	Namdaemun Market	110	6.3	8	Hangang River/Ferry	39	6.6
9	Gangnam Station	45	4.5	9	Cheonggyecheon	90	5.1	9	Jamsil (Lotte World)	36	6.1
10	Insa-dong	43	4.3	10	Garosu-gil Street	73	4.2	10	Cheonggyecheon	31	5.2
Total		1007	100.0	Total		1748	100.0	Total		591	100.0

Note: Multiple responses allowed.

Table 6
Comparing normalized degree centralities of tourist attractions in length of stay networks.

Rank	Short stay network Attractions (Normalized degree centrality)	Medium stay network Attractions (Normalized degree centrality)	Long stay network Attractions (Normalized degree centrality)
1	Myeong-dong (67.857)	Myeong-dong (67.857), Dongdaemun Market (67.857), Namsan/N Seoul Tower (67.857), Sinchon/Hongik Univ. (67.857), Itaewon (67.857), Jamsil (Lotte World) (67.857), Gangnam station (67.857)	Myeong-dong (64.286), Dongdaemun Market (64.286), Namsan/N Seoul Tower (64.286), Sinchon/Hongik Univ. (64.286), Hangang River/Ferry (64.286)
2	Dongdaemun Market (64.286), Jamsil (Lotte World) (64.286)		
3	Namsan/N Seoul Tower (64.286)		
4	Palaces (60.714), Sinchon/Hongik Univ. (60.714), Hangang River/Ferry (60.714), Gangnam Station (60.714)	Palaces (64.286), Museums (Memorial Halls) (64.286), Insa-dong (64.286), Cheongdam-dong/Apgujeong-dong (64.286), Hangang River/Ferry (64.286), Cheonggyecheon (64.286), Namdaemun Market (64.286), Garosu-gil Street (64.286)	
5			Insa-dong (60.714), Jamsil (Lotte World) (60.714)
6			Itaewon (57.143), Palaces (57.143), Namdaemun Market (57.143), Cheonggyecheon (57.143)
7	Insa-dong (57.143), Cheonggyecheon (57.143)		

networks, while Itaewon, Jamsil (Lotte World), and Gangnam station ranked first in the medium stay network, and Hangang River/Ferry ranked first in the long stay network. In contrast to the short-stay network, the medium- and long- stay networks exhibited multiple attractions tied for first ranking.

4.5. The distribution patterns of normalized degree centralities by length of stay

Fig. 4 geographically visualizes the distribution patterns of normalized degree centralities for first ranked tourist attractions in length of stay networks (i.e. short, medium, and long stay). Compared to short- and long-stay networks, medium-stay tourists tended to visit destinations located in southeastern Seoul (i.e. Gangnam Station, Jamsil/Lotte World).

4.6. Comparing normalized eigenvector centralities of tourist attractions in length of stay networks

Table 7 compares normalized eigenvector centralities of tourist attractions in length of stay networks. The normalized eigenvector centrality considers local network of attractions immediately adjacent to focal attraction(s). Thus, eigenvector centrality can be recognized as a more refined version of degree centrality (Prell, 2012).

Myeong-dong ranked first in length of stay networks (i.e. short stay, medium stay, and long stay). Thus, Myeong-dong constitutes a prestige attraction in the networks, i.e. all attractions located in Seoul depend on Myeong-dong. Nevertheless, Dongdaemun Market, Namsan/N Seoul Tower, and Sinchon/Hongik University also ranked first, along with Myeong-dong, in both medium-stay and long-stay networks. A difference between medium-stay and long-stay networks was that Itaewon and Gangnam Station ranked first in the medium-stay network, but Hangang River/Ferry ranked first in the long-stay network.

4.7. The distribution patterns of normalized eigenvector centralities for attractions in length of stay networks

Fig. 5 illustrates the geographic distribution patterns of normalized eigenvector centralities of attractions ranked first in length of stay networks (i.e. short, medium, and long stay). While diffusion patterns in the tourists' spatial behavior were observed, some interesting differences in the diffusion pattern were also identified. Overall, short- and long-stay tourists tended to travel more widely throughout the destination (Seoul) than medium stay tourists. Gangnam Station was less visited by long-stay than by short- and medium- stay tourists. On the other hand, Itaewon was less visited by short-stay tourists than by medium- and long-stay tourists.

4.8. Local Indicators of Spatial Association (LISA) for normalized degree centralities

The results of LISA analysis for normalized centralities are presented

Table 7
Comparing normalized eigenvector centralities of tourist attractions in length of stay networks.

Rank	Short stay network Attractions (Normalized eigenvector centrality)	Medium stay network Attractions (Normalized eigenvector centrality)	Long stay network Attractions (Normalized eigenvector centrality)
1	Myeong-dong (37.543)	Myeong-dong (33.362), Dongdaemun Market (33.362), Namsan/N Seoul Tower (33.362), Sinchon/Hongik Univ. (33.362), Itaewon (33.362), Jamsil (Lotte World) (33.362), Gangnam Station (33.362)	Myeong-dong (36.470), Dongdaemun Market (36.470), Namsan/N Seoul Tower (36.470), Sinchon/Hongik Univ. (36.470), Hangang River/Ferry (36.470)
2	Dongdaemun Market (37.393), Namsan/N Seoul Tower (37.393), Jamsil (Lotte World) (37.393)		Jamsil (Lotte World) (35.169)
3	Sinchon/Hongik Univ. (35.773)		
4	Gangnam Station (35.755)		Insa-dong (34.920)
5	Palaces (35.670)	Hangang River/Ferry (32.570), Palaces (32.570), Museums (Memorial Halls) (32.570), Insa-dong (32.570), Namdaemun Market (32.570), Cheonggyecheon (32.570), Garosu-gil Street (32.570)	Itaewon (33.436)
6	Cheonggyecheon (34.250)		Namdaemun Market (33.283)
7	Insa-dong (34.222)		Cheonggyecheon (33.219)

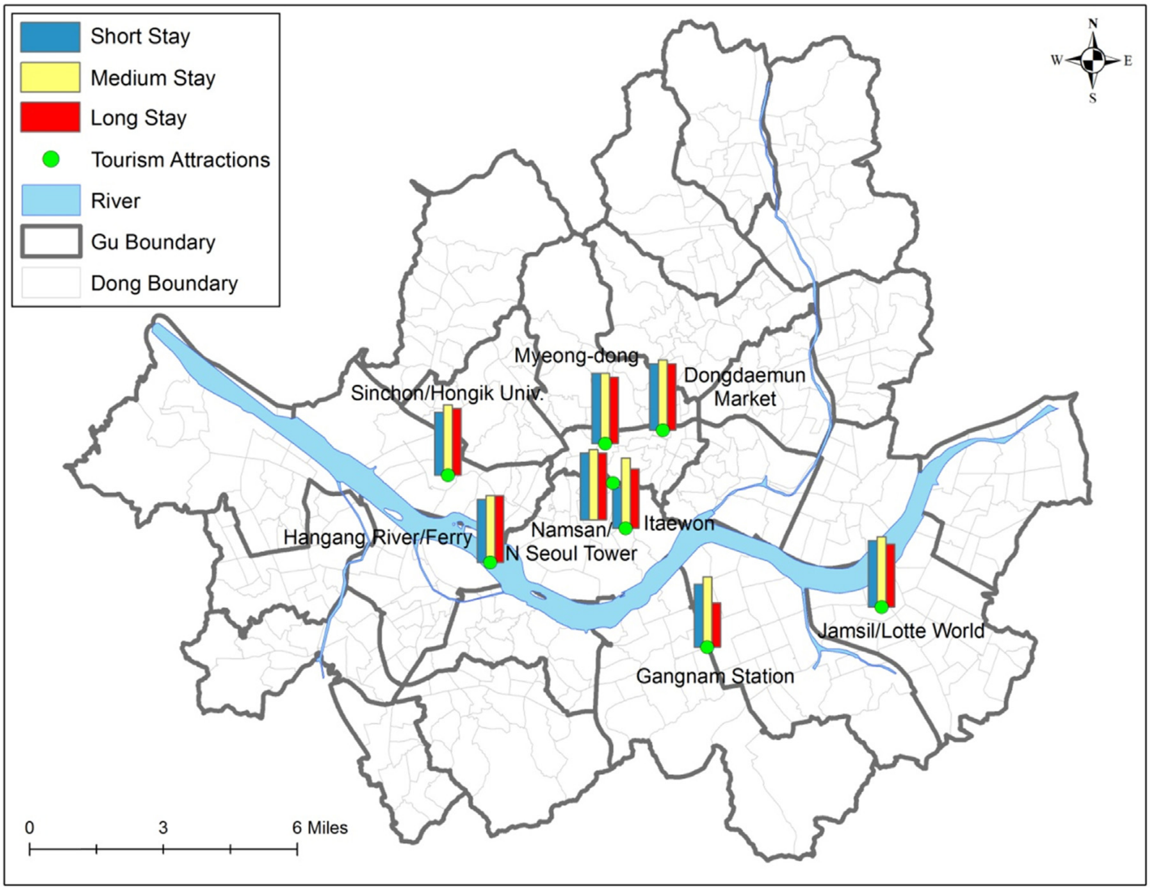

Fig. 4. Distributional patterns of the normalized degree centralities of central tourist attractions in Seoul, South Korea, by length of stay. Note: The map is an original product of the authors.

in Fig. 6. For short stay tourists, Myeong-dong, Dongdaemun Market, and Namsan/N Seoul Tower were identified as HH, which signifies significant hot spots that can be considered anchor-points of tourist attractions. Myeong-dong, Dongdaemun Market, and Namsan/N Seoul Tower were also found to be HH for medium- and long-stay tourists. However, Gangnam Station and Sinchon/Hongik Univ. were identified as HH for only medium- and long-stay tourists, respectively.

4.9. Local Indicators of Spatial Association (LISA) for normalized eigenvector centralities

The results of LISA analysis for normalized eigenvector centralities are presented in Fig. 7. While, overall, the LISA analysis results were consistent with the distribution patterns of normalized degree centralities presented in Fig. 6, an interesting finding is that Jamsil/Lotte World was identified as HH for medium-stay tourists.

5. Conclusion

5.1. Discussion

5.1.1. Theoretical implications

The most critical theoretical contribution of this study is applying the anchor-point theory developed by Golledge (1978) to tourist attraction system research, along with considering temporal heterogeneity (i.e. length of stay). In the approximately four decades since anchor-point theory was developed by the geographer Golledge, tourism researchers have taken little advantage of the theory's potential for explaining tourists' spatial behavior. This study successfully used it to identify anchor-points in Seoul, the capital city of South Korea. More importantly, this work reveals two meaningful results; first, the anchor-point attraction can be multiple rather than single, depending on the length of stay. Second, the attractions that serve as anchor points vary across the length of stay networks. As such, this study suggests that (1) a tourist attraction system can be hierarchically distributed; (2) there can be multiple anchor-point attractions within a destination; and (3) the influence of attraction systems' hierarchical nature on flows can be weakened by increasing trip length.

Understanding tourist attraction networks within a destination through tourists' spatial movement has been insufficiently pursued (Liu et al., 2017). This study investigated the nature of the locational position of tourist attractions within length of stay networks and compared differences in the locational position of attractions among the networks by employing normalized degree and eigenvector centrality measures. Like Liu et al. (2017) and Jin et al. (2017), this study also confirms that centrality measures can be useful to identify the vital attractions in a destination. Since attractions with high degree and eigenvector centralities are considered centrally located attractions in the network, those attractions can be used as strategically important attractions for distributing tourists to the other attractions of the destination.

While Leiper (1990) proposed that tourist attractions can be categorized as primary, secondary, and tertiary, this study demonstrates that primary attractions could be further classified hierarchically. For example, Myeong-dong was the core attraction for all networks, but for medium-stay networks, attractions such as Dongdaemun Market, Namsan/N Seoul Tower, Sinchon/Hongik University, Itaewon, Jamsil (Lotte World), and Gangnam Station are also identified as core attractions, ranked first in visitation frequency. Concerning the long-stay network, Dongdaemun Market, Namsan/N Seoul Tower, Sinchon/Hongik University, and the Hangang River/Ferry were also core. This

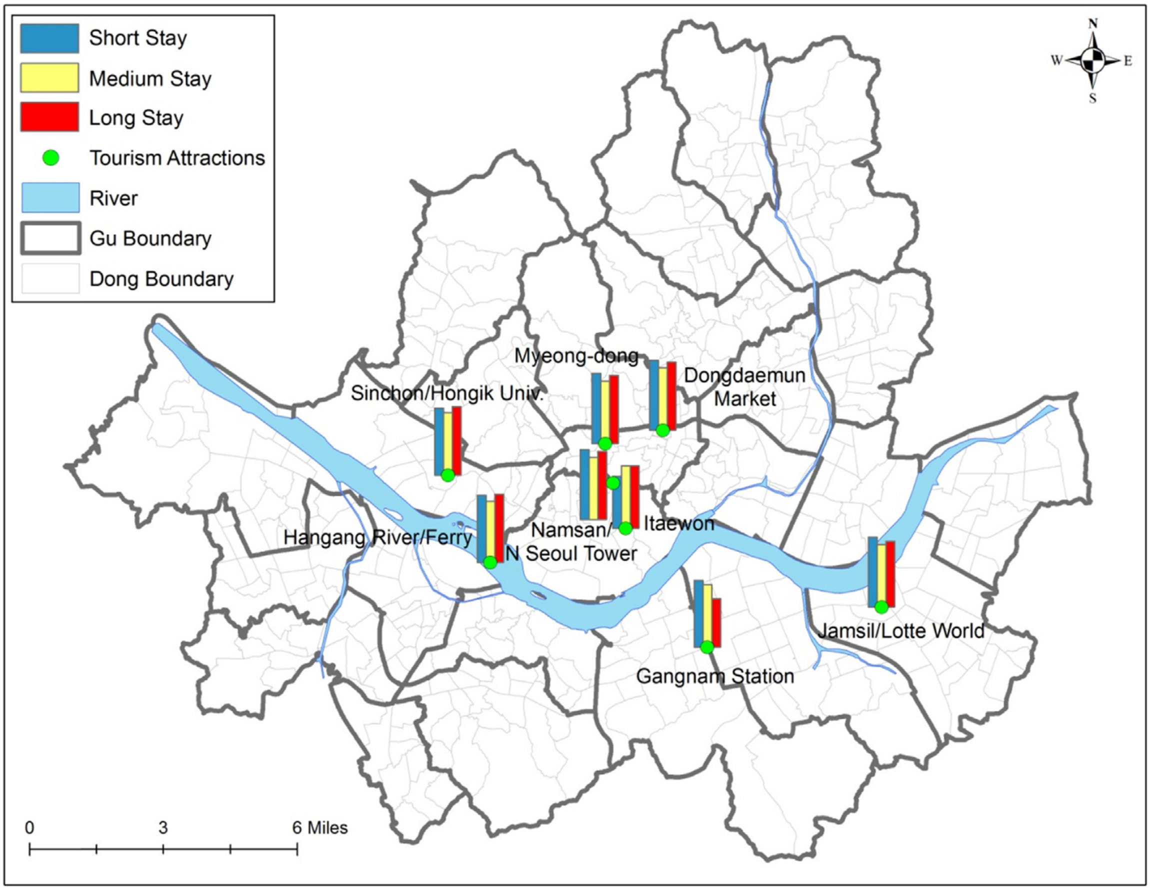

Fig. 5. Distributional patterns of the normalized eigenvector centralities for attractions in length of stay networks. Note: This map is an original product of the authors.

finding could help to concretize tourist attraction theory with anchor-point theory.

Attraction hierarchy can be linked with the notion of clustering (Leiper, 1990). The tourist attractions ranked first in the medium stay (i.e. Myeong-dong, Dongdaemun Market, Namsan/N Seoul Tower, Sinchon/Hongik Univ., Itaewon, Jamsil, and Gangnam Station) and long stay (i.e. Myeong-dong, Dongdaemun Market, Namsan/N Seoul Tower, Sinchon/Hongik Univ., and Hangang River/Ferry) networks are not geographically closely located, nor do they have a unifying theme. As noted by Leiper (1990, p. 375), "what is significant is the combination". This finding suggests that the hierarchy of attractions is not necessarily based on geographical proximity. Instead, the hierarchy can be structured by the anchoring roles attractions play within the entire network structure. In other words, the core attractions could vary depending on tourist' length of stay.

For both tourists and travel industry, programing and packaging for the best tourism experience, fundamentally constrained by length of stay, is a central concern. Another important finding from Oppermann (1994) study to consider is that shorter-stay visitors have higher per-diem expenditure, while longer-staying counterparts spend more per-capita expenditure in destination. Similarly, Lee et al. (2006) identified systematic relationships among length of stay, destination activity patterns, and the amount of money spent in destinations. These empirical evidences point toward the interplay of temporal heterogeneity and tourists' behavior, particularly their spatial movement which entails activity pursuit and expenditure. This study has a potential to make substantial contribution to related literature by revealing not only the network structure among attractions in a tourism destination but also varying roles of anchor-point attractions depending on temporal heterogeneity. The length-of-stay effect is not necessarily on the geographical closeness, nor is the thematic similarity of attractions. This finding suggests a new venue for research on the role that time constraint factor plays in determining the role each attraction plays and the hierarchical network structure of places in tourism destinations (Kang, 2015).

In addition, findings of this study suggest several methodological implications for effective tourism planning and development. This study identified the spatial structure of tourist attraction system in Seoul, South Korea. Specifically, this study explored the spatial distributional patterns of the degree of centralities (normalized degree centralities, normalized eigenvector centralities), allowing identification of the hot spots of tourism attraction networks in Seoul. Previous social network studies in tourism destination planning and development have typically addressed 'how the tourist attractions are connected to each other'. Using GIS-based mapping and spatial analytical methods, however, this study extended the focus from 'how the tourism attractions are connected to each other' to 'how the tourist attractions are connected to each other, and where'. The methodological integration of SNA and GIS can offer tourism developers a powerful technique through which to better understand local patterns of tourism attraction networks, ultimately providing geographical insights into place-based spatial strategy and marketing in the tourism industry.

5.1.2. *Practical implications*

The results of degree and eigenvector centrality analyses reveal that among all attractions in the networks, regardless of length of stay, Myeong-dong was the most influential and prestigious attraction for tourists. However, along with Myeong-dong some other attractions were also identified as central, meaning ranked first in the medium- and long-stay networks (see Tables 6, 7): Dongdaemun Market, Namsan/N

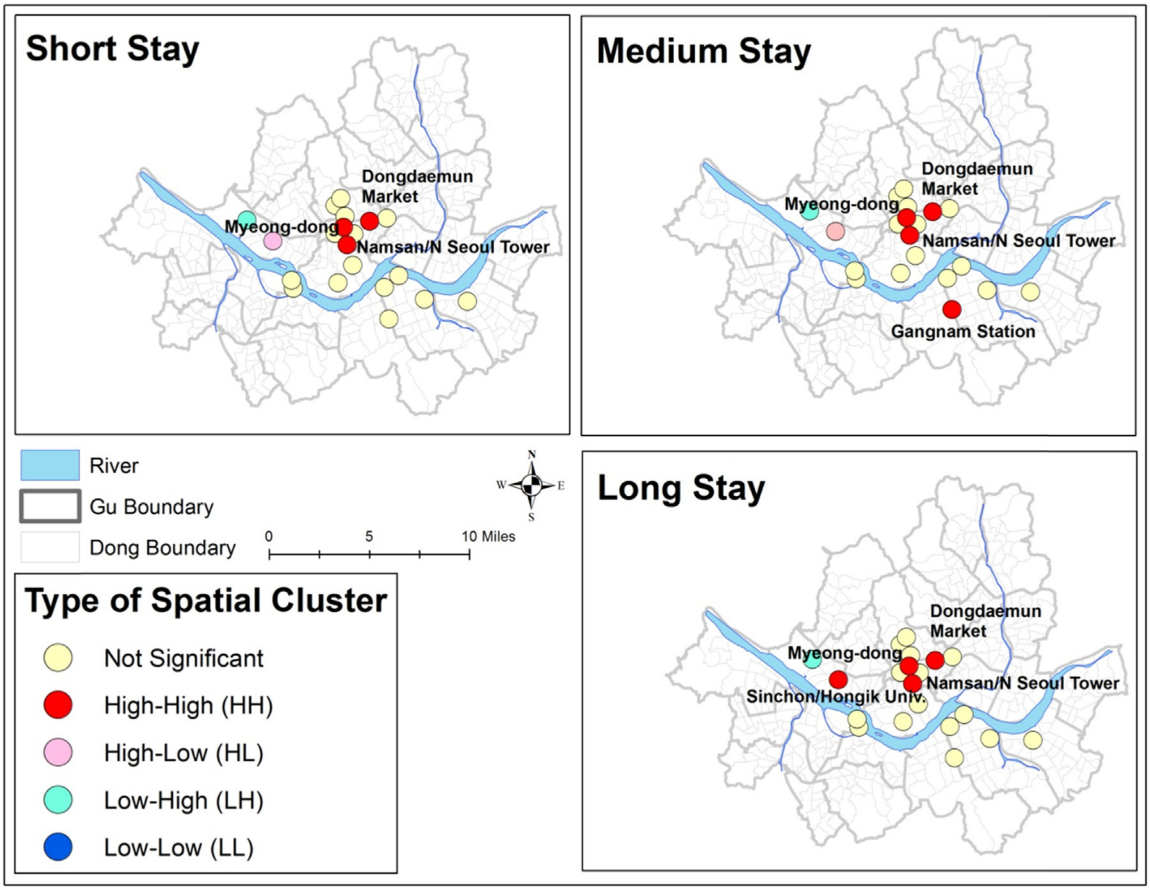

Fig. 6. Results of Local Indicators of Spatial Associations for normalized degree centralities. Note: This map is an original product of the authors.

Seoul Tower, and Sinchon/Hongik University. Interestingly, Itaewon, Jamsil (Lotte World), and Gangnam Station were identified as central attractions for the medium-stay network only, and Hangang River/Ferry was central only for the long-stay network. These results suggest that tourists' travel patterns and attraction types could be differentiated by their length of stay, which is supported by Jin et al. (2017), Kang (2015), and Shoval and Raveh (2004).

Attractions can be classified into categories such as cultural attractions, natural attractions, events, recreation, and entertainment attractions (Goeldner & Ritchie, 2006). Myeong-dong and Dongdaemun Market are famous shopping districts, while Namsan/N Seoul Tower, Sinchon/Hongik Univ., Jamsil (Lotte World), and Gangnam station are attractions where tourists can experience youth culture or contemporary metropolitan culture. Itaewon is a district where tourists can enjoy diverse and active international culture, entertainment, and shopping opportunities. From this point of view, the results indicate that Chinese FITs tend to prefer entertainment attractions.

More interestingly, Chinese FITs' spatial behavior in Seoul tended to expand according to their length of stay, indicating that anchor-point attractions were not essentially limited to the central area of Seoul. This result might indicate the importance of developing or promoting anchor-point attractions located in peripheral areas of Seoul for Chinese FITs, since Chinese outbound FITs tended to be middle class, relatively young, and relatively high in educational background and income, and their main motivation was sightseeing, similar to the outbound Chinese tourists studied by Xiang (2013).

However, these Chinese FITs tend to have low flexibility in their trips and desirous of experiencing a sense of freedom during their travel (Xiang, 2013). Chinese FITs do prefer not to venture into non-tourist places (Xiang, 2013). Thus, to facilitate multi-attraction travel, a destination marketing organization could distribute diverse tourism information to be used by Chinese FITs when preparing their trip plans at their homes. Tourism information could contain very specific information to help the FITs make specific sub-decisions during a trip, to allow them to experience a sense of freedom during a trip without changing their overall plans. In addition, providing reliable and useful tourism information to the FITs may encourage their traveling into non-tourist places, particularly attractions located in periphery areas in Seoul, as they may feel comfortable traveling in non-tourist places provided they have good tourism information.

This study shows that the centrality measure would be a relevant data analysis technique for identifying major attractions located within a destination compared to simple frequency counts. While all tourists might not necessarily visit a single attraction during their trip, some tourists tend to visit multiple attractions during a trip. For this reason, a relational and collaborative approach between/among tourist attractions would be recommended to better measure tourists' actual travel patterns and frequency, which could contribute to better understanding of tourists' spatial behavior for implementing destination development, marketing, and management strategies (Fyall, Garrod, & Wang, 2012; Nguyen & Pearce, 2015; Wang & Xiang, 2007; Yang, 2017; Żemła, 2014).

5.2. Limitations/suggestions

In interpreting the findings of this study, several limitations should be noted. First, since the study data did not contain directional information, two of the three centrality measures, betweenness and closeness centralities, were not computed. If directional data become available, future studies should calculate in- and out-betweenness and closeness centralities by considering the direction of tourists' movement between/among attractions.

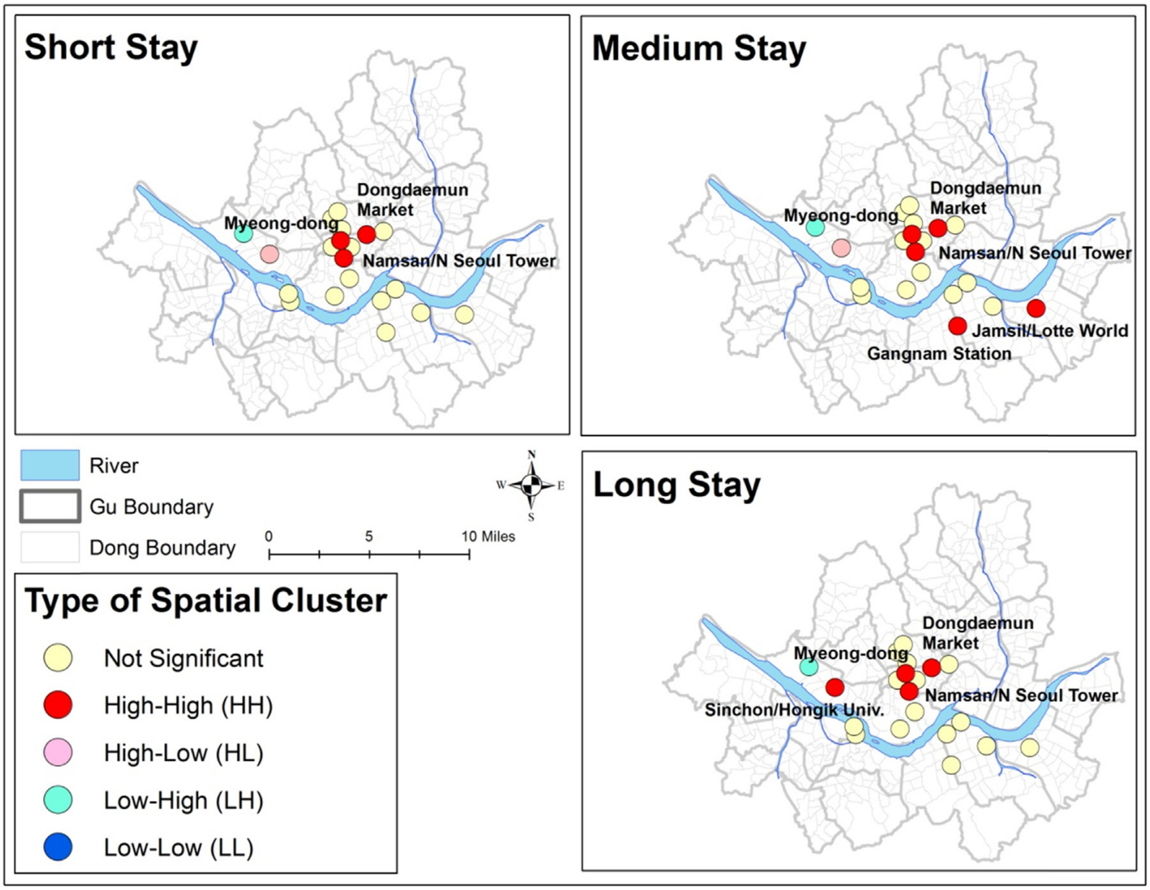

Fig. 7. Results of Local Indicators of Spatial Associations for normalized eigenvector centralities. Note: this map is an original product of the authors.

Second, this study focused on tourist attractions within Seoul, the capital city of South Korea. While Seoul could be an exemplar destination with diverse attractions and a relatively large spatial scale, implications of this study might not immediately apply to other destinations, because the spatial structure of each destination is different. Nevertheless, this study is not a pure case study. This study was designed based on an interesting geography theory, i.e. anchor point theory, and it tested that theory using SNA techniques. For this reason, the possibilities for generalizing the results is considerable. This study showed anchor-point attractions can be changeable depending on tourists' socio-economic, motivational, and constraints characteristics. Further studies in other geographic regions are called for, to advance anchor-point theory from a tourism perspective.

Third, this study used raw data from the International Visitor Survey produced by the Korean Ministry of Culture, Sports, and Tourism for finding anchor-point attractions within a large metropolitan area, along with a consideration of the natural connections between/among attractions using SNA. For this, the data set was suitable. However, the recent development in the analysis of tourists' spatial behavior within a destination has been supported by technologies to track tourists' movement in space and time, such as Global Positioning Systems (GPS). Thus, future study might consider applying GPS for collecting tourists' spatial behavior data, meaning visitation patterns. These data could be applied to better identify the combination of tourist attractions along with collecting tourists' trip, demographic, socio-psychological characteristics such as the length of stay.

Fourth, anchor-point theory addresses spatial knowledge, since the theory focuses on the relative significance of each attraction (Golledge & Stimson, 1997). Tourists' levels of spatial knowledge might differ depending on their trip career, socio-economic, and/or demographic characteristics. Thus, future studies might examine the relationship between tourists' level of spatial knowledge related to the destination and anchor-point attractions.

Lastly, this study considered Chinese FITs only. Other nationalities and groups of tourists were intentionally excluded from the analyses. Thus, the findings of this study might be limited to understanding the spatial behavior of Chinese FITs to Seoul, South Korea. Future studies might consider diverse tourist types with other nationalities and groups to better identify the spatial structure of tourist attraction networks in Seoul.

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