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Analyzing travel mobility patterns in city destinations: Implications for destination design

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ABSTRACT

Understanding the features of travel activities is important in elaborating travel behaviors and segmenting travelers based on the similarity of activity patterns. This research applying mobile big data analytics suggests a novel method to classify travelers by considering the sequences of travel activity with individuals' trajectories. The result revealed five distinct travel types visiting city destinations and demonstrated dynamic travel flow among different mobility types. Recognizing that different types of travel patterns present important information in understanding destinations' roles (or functions), this study attempts to characterize the functionality dynamics of city destinations based on travel activity types. As a result, the findings of this research provide insights into the demand-driven construct (or flow-based) of destination planning, which is the foundation of smart destination design. In addition, important methodological and practical implications that could be useful for city destination planners/designers are suggested.

1. Introduction

Travelers consume destinations differently, and these differences are reflected in distinct movement patterns (McKercher, Wong, & Lau, 2006). Travel movement patterns comprise travelers' sequential activities through space and time (Lau & McKercher, 2006). Several scholars in tourism have conducted research to identify typologies and structures and to predict the patterns of travel movement (Vu, Li, Law, & Ye, 2015; Xu, Li, Belyi, & Park, 2021; Zhao, Lu, Liu, Lin, & An, 2018). However, relevant studies have focused mainly on characterizing mobility patterns based on spatial and temporal dimensions rather than attempting to shed light on travelers' activities. Nevertheless, understanding the features of travel activities is important in elaborating travel experiences, comprehensively explaining travel behaviors, and classifying travelers based on the similarity of activity patterns. In this vein, McKercher et al. (2006) stated that the consumption styles of travelers at the destination should be reflected by and be reflective of differences in movement patterns.

Given the context of increasingly varied tourism products and competition (Dwyer, 2015; Fyall, Garrod, & Wang, 2012), tourists' time allocation and spatial movement have become more complex and diverse (Park & Zhong, 2022). Researchers have long seen the need to classify tourist movements before analyzing destinations (Cohen, 1972; Dann, Nash, & Pearce, 1988; Pearce, 1982; Plog, 1974). Various studies have attempted to classify tourists using tourist characteristics, including individual sociodemographic profiles (Keng & Cheng, 1999; Nguyen & Cheung, 2014) and travel purposes (Coccossis & Constantoglou, 2008). Most previous works have relied on behavioral surveys based on questionnaires and focused on the psychographic aspects of travelers. These data are not always sufficient for measuring precise travel movements in spatiotemporal dimensions, especially when exploring large study areas and long study periods. Survey data can hardly support a systematic classification of all types of entire tourists within a destination, which is not conducive to mapping visitor use of the destination from a comprehensive view. With location-based services advancing rapidly, tourism researchers have a great potential to

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capture the location footprints of large populations, allowing them to extract travel behaviors at an unimaginable scale (Asakura & Iryo, 2007). Indeed, the advancement of information and communication technology has provided tourism researchers with a golden opportunity to access big data consisting of data collection, exchange, processing, and analytics (Park, 2021). Due to practical constraints in collecting behavioral data at the during- and post-trip stages, tourism researchers used to focus mainly on the travel behaviors at the pre-trip stages. The benefits of mobile devices enabling travelers to bring technology to any place and any time allow researchers to obtain real-time and continuous information on travel information, communication, and movement behaviors (Li, Xu, Tang, Wang, & Li, 2018). In particular, mobile positioning data are one of the trajectory big data, which involve a continuous trip of individuals that can support researchers in further understanding the time allocation and space movement of visitors to different activities (Ahas, Aasa, Mark, Pae, & Kull, 2007, 2008). Although many studies have been conducted to differentiate tourist movement patterns within and among destinations by using mobile phone data (Girardin, Calabrese, Dal Fiore, Ratti, & Blat, 2008; Hardy et al., 2017; Zhong, Sun, & Law, 2019; Zhu, Sun, Yuan, Hu, & Miao, 2019), less attention has been given to the semantic information of different types of tourist activity, such as travel purposes. Hence, this study suggests a novel approach to analyze travel mobility, from mobile phone big data (or consumption styles within a destination).

Furthermore, different travel patterns present important information in understanding destinations' roles (or functions) (Ahas et al., 2007; Leiper, 1979). Insights on travel mobility patterns can facilitate the characterization of destination functionality dynamics in terms of spatial and temporal dimensions, which help destination marketing organizations capture the hidden features of structural tourism patterns. C. Gunn (1997) initiated a new perspective of place design, focusing on travel's whole landscape in his book "Vacationscape: Designing Tourist Areas." Identification of regional functions in the destination (or functions in space), such as cultural, natural, authentic, and structural functions, is a fundamental step in enhancing land use planning and design of travel destinations (Beritelli & Laesser, 2017). Indeed, this insight derived from travel flow and activities enables tourism researchers to detect different functional orientations of city destinations and understand travel destinations from the perspective of how visitors experience (or consume) it, which becomes the foundation of tourism design (Park, Xu, Jiang, Chen, & Huang, 2020). Moreover, analyzing the spatial interactions between destinations, including different functionalities, sheds light on accomplishing smart tourism designs. Therefore, this study aims to (1) systematically classify tourists based on their travel mobility patterns, (2) compare differences in the composition of traveler types between district destinations (hereafter destinations will refer to district destinations, unless otherwise stated), (3) detect regional roles and features of destinations based on the configuration of traveler types, and (4) explore the spatial interactions among different destinations by uncovering how these different types of tourist move between them. This study analyzed a large mobile dataset in Seoul, the Republic of Korea (hereafter, Korea) and applied advanced spatial analytic algorithms to address these research purposes.

2. Literature review

Tourism scholars have suggested numerous methods and facilitating factors to classify travelers and thus understand better and predict their travel behaviors. Relevant literature on tourism segmentation can be categorized into two classes, namely, conceptual (i.e., a priori or commonsense segmentation) and data-driven (i.e., a posteriori) approaches (Dolnicar, 2002). The conceptual approach generally proposes a typology in which the variable(s) to group the travelers are recognized before the analysis is applied, such as demographic and behavioral intentions. The data-driven segmentation depends on the results of the data analysis to obtain insights on segmentation after the analysis is conducted. The previously unknown size and the number of travel segments can be identified by performing statistical analyses (e.g., factor analysis or cluster string analysis). More specifically, the typical studies of commonsense segmentation attempt to profile travelers based on the origin countries (i.e., geographic segmentation), demographic characteristics, and certain travel activities (e.g., shopping tourists and green tourists (Bign'e et al., 2008; Juaneda & Sastre, 1999; Moscardo, Pearce, & Morrison, 2001). For example, McKercher (2001) classified travelers according to their visiting patterns, such as visitors who achieve main travel activities at a destination and those who travel through the place. The study presented heterogeneous demographic and travel behaviors/motivations at the destination between two segmented groups. Klemm (2002) considered ethnic characteristics when segmenting travelers and showed different travel preferences and interests between different ethnic features.

Following data collection and access acceleration, tourism researchers will likely adopt the data-driven segmentation method. Bieger and Laesser (2002) attempted to segment travelers based on motivation factors by employing statistical methods, such as clustering and discriminant analyses. Accordingly, they proposed four groups of travelers with different travel motivations and presented different travel profiles among the traveler segmentations. Similar approaches to travel classification/segmentation have been largely conducted based on destination involvement (Hu & Yu, 2007), preferences (Lang & O'leary, 1997), benefits (Yannopoulos & Rotenberg, 2000), information searching behaviors (Park & Kim, 2010) and the usage of social media (Amaro, Duarte, & Henriques, 2016). Studies on tourism segmentation have been identified to have actively explored travelers' perceptions, primarily, psychographic aspects of individuals, to group respondents and used travel activities/behaviors to demonstrate the different profiles of segmentation groups. Essentially, this study highlights the importance of behavior-based segmentation based on the statement that travel behavior reflects individuals' interests, preferences, and motivations sought at the destinations (Debbage, 1991; Haustein, 2012; Levitt, Zhang, DiPietro, & Meng, 2019). Dolnicar and Fluker (2003) analyzed past destination visitation patterns—surfing activities—as a segmentation base. Shani, Wang, Hutchinson, and Lai (2010) attempted to segment travelers based on expenditure patterns, such as light, medium, and heavy spenders. Park, Wang, and Fesenmaier (2011) investigated online purchasing patterns of travel products. They explored multi-travel products comprising eight items and examined dynamic purchasing behaviors according to different product categories. The study proposed three segmentation groups, namely, core, advanced, and comprehensive Internet travelers, by considering the number and types of products purchased and the order of the products consumed. From the perspective of behavior-based segmentation, this research suggests the usefulness of travel mobility patterns (or spatial behavior) as a criterion for segmenting travelers. Travel mobility is associated with time availability, cost, and individual propensity to travel to culturally or spatially distant places (Crouch, 1994). Spatial behavior serves as an effective proxy of tourist personality or typology (Debbage, 1991). Travel movement results from mental images and cognitive processes that affect individual personality and motivation. Thus, understanding the travel flow helps tourism researchers explain the dynamics in the market mix at destinations, which ultimately account for different travel behaviors/activities (McKercher, Chan, & Lam, 2008), and possibly relate life cycle and social class dimensions (Nyaupane & Graefe, 2008). The existing relevant literature has largely focused on "travel distance" as a factor of spatial behavior to segment travelers. Some segments of travelers are sensitive to travel distance, whereas others are distance-resilient. Classification/segmentation showing different distances traveled has been explored according to different countries of origin (Reid & Reid, 1997), sociodemographic factors (Debbage, 1991), and travel activities/motivations (Moutinho & Trimble, 1991). These prior studies suggested that distance, as an indicator of travel flow, strongly predicts travel behavior (McKercher, 2001). The evolution of mobile technology that provides rich and precise data for spatiotemporal information of travelers accelerates the understanding of individual movement patterns within an environmental setting. It identifies people's activities in place (Park et al., 2011). This advancement enables tourism researchers to attempt the flow-based segmentation of travelers. Scholars have highlighted the importance of destination design rather than destination planning and considered it an essential activity in contributing to the success of tourism destinations (Xiang, Stienmetz, & Fesenmaier, 2021). C. Gunn (1997) introduced a new perspective on place design, focusing on the whole landscape of travel with travel experiences as opposed to the assortment of fragmented approaches in his book "Vacationscape: Designing Tourist Areas." More specifically, vacationscape refers to an important advance in destination planning with emphasis on place design, destination as a system, the holistic tourist experience, and the analytical approach to understanding tourists' dynamic needs and behavior. When C. Gunn (1997) introduced design principles and discussed topics of destination planning in his book, he stressed functional design as the first element, considering a destination's structural, physical, and cultural functionalism. Understanding the structure of travel flow is fundamental to building a functional design in space and conceiving tourism production and performance (Beritelli, Reinhold, & Laesser, 2020; Xiang et al., 2021). Beritelli and Laesser (2017) conceptualized destination as a demand-driven construct to design interventions in tourist places and emphasized approaches to assess multiple dynamic functions in destination by analyzing travel flow.

In this vein, e Silva et al. (2021) attempted to classify European regions and proposed regional tourism typologies, such as cities, coastal, mountains and nature, and rural and urban mixes based on the locations of accommodations. However, in response to e Silva et al. (2021), Camară (2022) argued that the method for categorizing regions, tourism regionalization, is a complex process, which implies that considering one of supply in tourism (i.e., accommodation) is restricted to bring about a comprehensive regional tourism typology (Hernández-Martín et al., 2016). Instead, the reflection of travel behavior and activities is essential to create the specificity of a tourist region.

Tourism scholars have identified diverse factors to classify/segment travelers. However, research has scarcely focused on analyzing the features of travel mobility (or spatial behaviors) due to limited access to data illustrating travel movement. Furthermore, despite some of the existing literature on market segmentation that considers travel mobility, their main focus has been on travel distance rather than specifically exploring structures of travel movement patterns. Consequently, this study investigating a large set of mobile positioning data proposes a novel method to classify travelers based on the semantic sequences of travel activity and understand dynamic travel behaviors between different travel types. Then, the composition of travel types facilitates identifying destination functions and shedding light on dynamic functional interactions between multiple destinations by travel flow.

3. Research context

The vacationscape is formed by strategic decisions in spatial planning that are co designed by individual beliefs and social practices of tourists and local communities (Scuttari, Pechlaner, & Erschbamer, 2021). The approach to involving design in planning ideas derives from Gunn's statement that "the integration of design activity is essential" (Gunn & Var, 2020, p. 337) when participation of communities is considered. Such as idea is not just involved in the participation processes. Instead, the inclusion of design links the spatial aspect referring to "a preferred pattern of land use" (Dredge, 1999, p. 773) with the place-making processes. Lew (2017) stated that tourism destination planning and marketing are place-making actions with the purpose of forming the image of and shape the imageability of a place/destination. Place-making involves a social composition of areas such as nature, place, history, and culture (Hultman & Hall, 2012), and the place-making processes can depend on tourist mobility patterns and experiences (Beritelli et al., 2020), and online social media technologies (Fesenmaier & Xiang, 2016). In this perspective, Beritelli et al. (2020) emphasized a trip flow-based perspective of destinations that explains how travel trajectories and key activities produce a temporal structure and spatial sense in travel flows as a framework of smart destination design. The flow-based view considers a destination as a heterogenous experience scape, including multiple and parallel supply networks associated with the co-presence of visitor flows (Reinhold, Laesser, & Beritelli, 2019). Understanding spatial travel movement and associated decision-making processes are fundamental to addressing the demand-driven construct of destination design interventions in tourist places. In this vein, this study explores travel movement patterns by not only considering spatial structure but also estimating semantic activities of visitor flow and thus proposes the segmentation method by grouping similar movement patterns (i. e., the first and second research purposes of this research). Urban functional regions indicate where human activities occur, such as land for residential, commercial, and industrial purposes (Xing & Meng, 2018). The urban functional regions are considered regional functions of the city destinations that play an important indicator in designing place environments and managing the destination resources (Louail et al., 2014). Detecting the regional functions and classifying the regions with similar functions is essential for discovering the characteristics of city destinations consisting of different socio-economic features and physical properties (i.e., travel attractions) (Pei et al., 2014). Accordingly, this research suggests an innovative approach to detecting the regional roles and features of destinations based on the configuration of traveler types defined from the structure of travel movement patterns above (i.e., the third research purpose of this research). Furthermore, this research sheds light on the spatial interactions among different destinations derived from the movement of different traveler types (i.e., the fourth research purpose of this research).

4. Analytical framework

This part describes the sequential process of the analytical framework including (1) the way to extract activity sequence of individual travelers from mobile phone trajectories; (2) the method to classify travelers into different types based on how they organize activities within and across different areas (e.g., districts in the context of the case study) of a city destination; (3) an analysis on the composition of travelers to gain insights into the functional characteristics of these districts; (4) a spatiotemporal analysis to better understand the temporal dynamics and spatial interactions of travelers' movement patterns. The details are shown in Fig. 1.

First, to extract meaningful periods of stays for individuals, an anchor point extraction method is used to transform international travelers' cell phone trajectory into an activity sequence. A labeling process is used to categorize travelers' stay or movement patterns. Although spatiotemporal data cannot contain semantic information about individual activities (e.g., surveys), the labeling process can provide an efficient scheme to reveal the semantic information embedded in travelers' mobile phone trajectories. It also complements the problem of missing contextual information due to big data deficiencies.

According to the activity sequences of individual travelers, several generic rough classifications are derived: first-day, last-day, returner, full-day, and same-day. These classes help reveal the heterogeneity of different individuals within the city to consume the destination. The key point is that these categories can map different functions that cities offer visitors. This time-based classification is generalizable across destinations (or districts) and can quantify the differences in travel composition between destinations (or districts). Then, on the basis of the proportion of different types of travelers within the destinations, the destinations are divided into different functional orientations to help better understand the destinations from the perspective of how visitors use it.

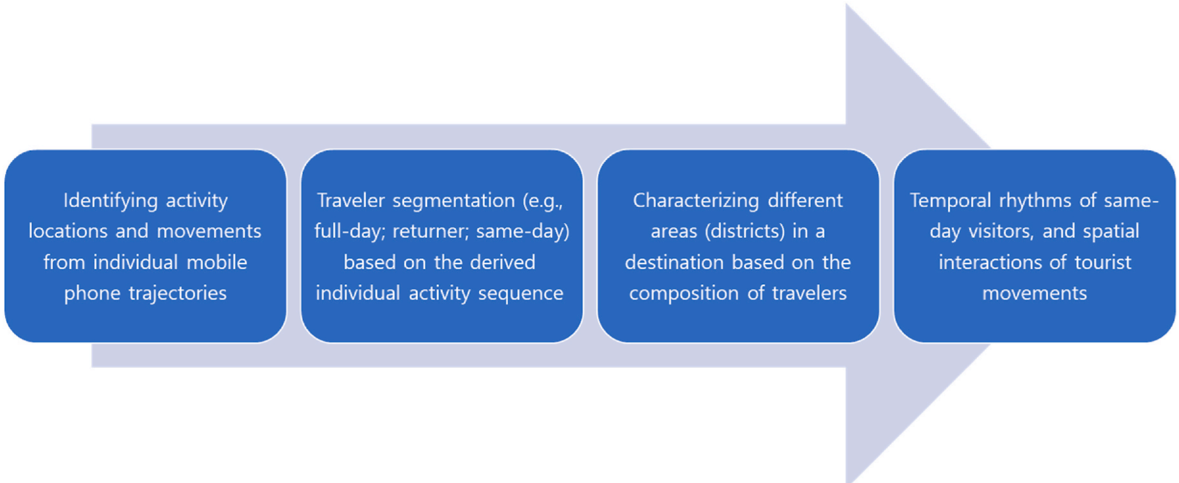

Fig. 1. Analytical framework.

The same type of visitor is found to have different intra-destination activity patterns of activity within different destinations. This study presents the patterns of same-day tourists visiting different destinations, including their entry and exit times, duration of stay, and frequency of return, all of which can reflect the pulse and rhythm of the city destination and help researchers paint a comprehensive picture of the destination image.

Interaction values between different functionally oriented destinations are defined. Inter-destination trips with a specific purpose are filtered to map the intensity of functional interactions between city destinations, namely, interaction values. Quantifying the actual movement between different city destinations helps in further understanding the spatial interaction between places from different functional perspectives.

5. Research design

5.1. Study area and dataset

The mobile dataset was acquired from a major cellular operator in Korea. It captures the mobile phone traces of 147,526 international travelers who visited the Seoul Special City (Fig. 2A, referred to as Seoul hereafter) between August 1 and 15th, 2018. The dataset documents phone users' location footprints as a series of stays at the cell tower level. Each record in the dataset documents the ID of a particular user, the observation date, the mobile base station (long/lat) where the phone was observed, and the start and end times that define the duration of a stay. Table 1 demonstrates a mobile phone user's records. As can be seen from the first two rows, the mobile phone user was observed at two

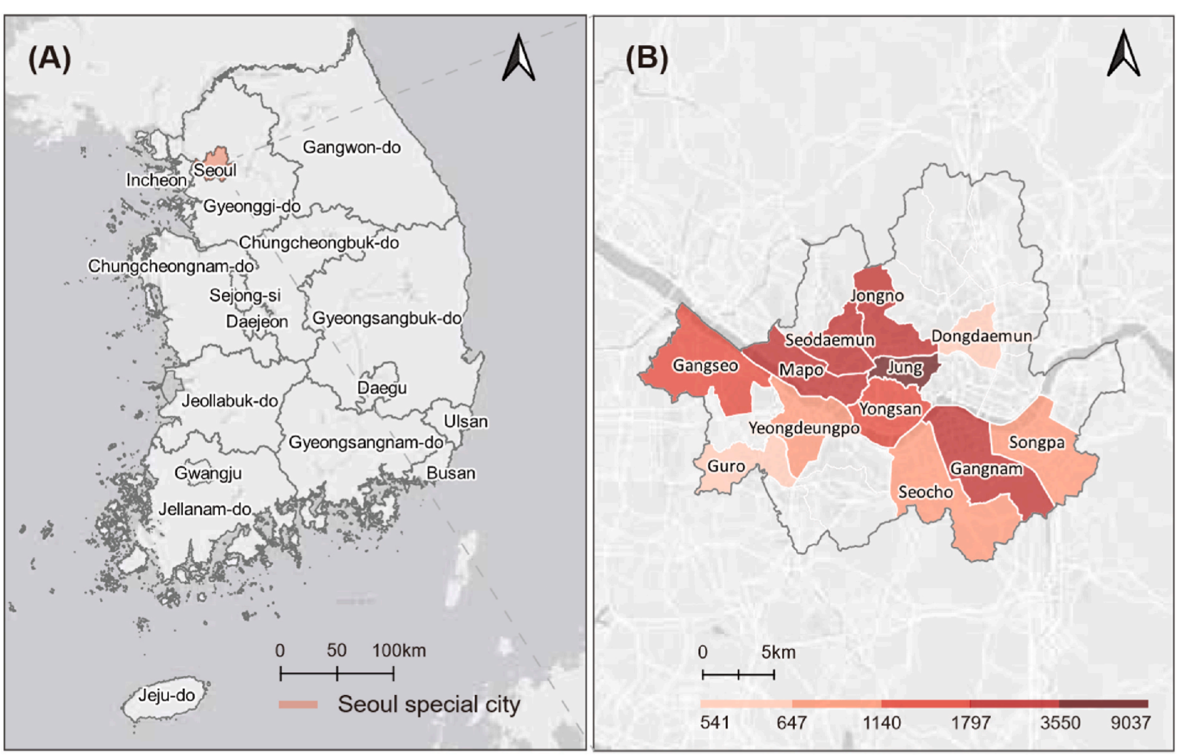

Fig. 2. (A) Provincial-level divisions of South Korea and the location of Seoul Special City; (B) Districts in Seoul with more than 500 average daily visitors identified from the mobile phone dataset.

Table 1
Example of a mobile phone user's records in the dataset.

User ID	Date	Starting Time	Ending Time	Longitude	Latitude
345 ***	2018-08-01	01:14:00	08:57:00	127. ***	35. ***
345 ***	2018-08-01	09:47:00	10:41:00	127. ***	35. ***
345 ***	2018-08-01	12:24:00	15:17:00	127. ***	35. ***
345 ***	2018-08-03	16:08:00	20:07:00	127. ***	35. ***
345 ***	2018-08-03	22:49:00	23:43:00	127. ***	35. ***

different locations from 01:14:00 to 08:57:00 and 09:47:00 to 10:41:00. The user possibly conducted a trip between two places associated with different coordinate information. According to the administrative division of Korea, Seoul is the largest metropolis in the country and is composed of twenty-five districts (i.e., city destinations: *Gu*). Through an exploratory analysis, we find that travelers seldom visited some districts. Therefore, we limit our analysis to the top 12 districts with an average daily number of visitors greater than 500 (Fig. 2B). These top 12 districts combined accounted for more than 90% of all travelers identified from the mobile phone data.

5.2. Identifying travelers' activity locations from mobile phone trajectories

To understand how travelers organize their activities in a day, the initial step is to identify where their activities are conducted. Due to cellphone load balancing (Isaacman et al., 2012), a traveler's observation in the mobile phone trajectory could switch between adjacent cellphone towers even when the traveler does not move. To mitigate these issues caused by positional uncertainty, we introduce the notion of activity anchor point to represent a set of cellphone towers in close proximity where a user has stayed for a certain amount of time (Xu, Li, Xue, Park, & Li, 2021).

A traveler's mobile phone trajectory can be represented as $T = \{(l_1, t_1^s, t_1^e), (l_2, t_2^s, t_2^e), \ldots, (l_n, t_n^s, t_n^e)\}$. Here l_i represents the cell tower location of the i^{th} record, and t_i^s (start time) and t_i^e (end time) defines the duration of stay at the corresponding location. To identify activity locations from$T$, we first sort all cellphone towers in T based on total duration of stay. We identify the cell tower with the longest stay duration and group all other cell towers within a distance of Δd into a cluster. For the remaining cell towers which are not grouped, we pick the one with the longest stay duration and repeat the clustering until all cell towers are grouped. These clusters are referred to as the individual's activity anchor points. The value of Δd should be made by considering the density of cellphone towers in the study area. By computing the Euclidean distance from each cell tower to its nearest cell tower, we find that the median and average values are 138.5 and 155.5 m, respectively. Therefore, we choose Δd as 500 m such that nearby cellphone towers where a traveler was observed can be grouped into the same cluster to form a meaningful activity location (i.e., anchor point).

By performing the anchor point extraction for each traveler, we transform each traveler's raw mobile phone trajectory (T) into a sequence of activity anchor points, denoted as $T^{'} = \{(r_1, t_1^s, t_1^e), (r_2, t_2^s, t_2^e), \ldots, (r_n, t_n^s, t_n^e)\}$. Here r_i stands for the i^{th} activity location by the traveler, and t_i^s and t_i^e denote the start and end times that collectively define the duration of stay at r_i . The activity sequence $T^{'}$ of travelers will be used in the next stage to derive their activity semantics. It will be further used to identify different traveler types (e.g., overnight stayers vs. same-day visitors).

5.3. Segmenting different types of travelers

Many previous studies suggest that mobile phone data can be used to identify important activity locations of residents, such as one's home and workplace (Xu et al., 2015). Similarly, the mobile phone trajectories of travelers here can be used to estimate dwelling place (i.e., accommodation) if they choose to stay overnight in a district (or a city destination) or identify same-day visitors to a district and where their activities were conducted. Such information is useful in describing how a particular district is used or consumed. For example, some districts may attract a lot of overnight stayers while others are more attractive to same-day visitors.

Given an individual's activity sequence $T^{'}$, we first parse the sequence into segments based on the circadian cycle (i.e., a 24-h day). For each segment that covers observations within a day, we used the method introduced by a previous study based on mobile phone data (Xu, Li, Xue, et al., 2021) to categorize their movements or activities into a few categories:

- Nighttime anchor point (NAP): NAP refers to the location where a traveler spends most time between midnight and 7 a.m. For an overnight stayer, the NAP is likely to be the person's accommodation place. We label the activity anchor point with the longest stay duration as NAP if the stay duration between midnight and 7 a.m. is over 3 h. The reason for imposing this threshold (3 h) is that some same-day visitors may also arrive at a district before 7 a.m., therefore leaving activity footprints that do not correspond to the accommodation place. Incorporating this threshold allows us to label a location as NAP only when a traveler spent a sufficient amount of time at this location. Note that an additional step is needed to tackle overnight stayers during their first day of visits to a district. For example, some travelers may arrive in a district after 7 a.m. and check in at a hotel in the afternoon or evening. Therefore, we first try to identify the traveler's NAP of the second day. If a NAP exists, the same location on the first day will also be labeled as NAP.
- Other activities (ACTIVITY): Once the NAP is identified, all other activity locations are labeled as ACTIVITY. These locations describe where travelers conducted their activities regardless of whether they are overnight or same-day visitors in a district.
- Travel (MOVE): This category describes travelers' movements between consecutive activity locations that occur within a particular district.
- Out of the current district (OUT): This category is used to label the proportion of time where the traveler is not observed in the target district. For example, a same-day visitor may arrive in a district on 15:30 and left on 18:00. The time before 15:30 and after 18:00 will be labeled as OUT.

Thus, A traveler's daily arrangement can be represented as a series of activities (NAP, ACTIVITY, MOVE, and OUT) in chronological order. Based on such semantic information, for a district M and on an observation day, we introduce several criteria to classify travelers into five categories.

- **Full-day visitor**: Individuals whose activities and travels fell completely within the district M (i.e., a city destination) during a 24-h day.
- **Returner**: Travelers who started the day (e.g., at the NAP) in district M, headed to other districts during the day, came back to M and stayed until the end of the day. This type mainly captures travelers who stayed overnight in a district but visited other districts during the day.
- **First-day visitor**: Travelers who visited district M for the very first time and stayed in the district till the end of the day. This type mainly captures the first day of overnight stayers in a district.
- **Last-day visitor**: Overnight stayers who left district M (e.g., checked out from the hotel) and did not return.
- **Same-day visitor**: Travelers who were not in district M at the beginning and end of the day but visited the district during the day. No NAP is detected for these travelers in the district. This type captures travelers who do not stay overnight but visit the district temporarily.

To better illustrate the concepts, we provide two examples for each type of traveler in Fig. 3. The activity sequence of a traveler is visualized during a 24-h day. The red denotes that a traveler was at the NAP (i.e., accommodation place), and the yellow represents a portion of time spent at ACTIVITY locations. The blue color denotes travel movements among locations, while the black denotes periods when a traveler was out of the target district *M*.

With this approach, we can identify all travelers who visited a district in a day as one of the five categories. For example, Fig. 3F shows the result of five types of travelers identified in district *Guro* on August 2, 2018. To improve the readability of the diagram, we adopt an agglomerative hierarchical clustering algorithm introduced by (Xu, Li, Xue, et al., 2021), such as travelers with similar activity sequences within the same type being positioned together. As a result, the diagram portrays the composition of travelers in the district. For example, there are two distinct sub-categories of first-day visitors, with one group of visitors tending to check into the city at around 14:00 and the other tending to stay in the city from 18:00 and onward. Using this methodological framework, we repeat the analysis for all districts on each observation day during the study period (August 1 to 15th, 2018).

6. Results

6.1. Composition of five types of travelers in the districts

The approach developed above empowers us to characterize districts through the composition of travelers. For each district, we compute the daily average number and percentage of five types of travelers, as shown in Table 2. Districts are sorted in descending order based on average daily total visitors. According to the results, districts show diverse characteristics. Some districts tend to attract more Full-day visitors or Returners, while others are more attractive to Same-day visitors. In general, Full-day visitors account for 2.5%–11.6% of total visitors in these districts, compared to 5.1%–18.5% for Returners. Same-day visitors account for a large fraction of travelers in these districts, but the exact share varies substantially. For instance, in Songpa, 71.5% of the travelers are Same-day visitors, while this number is only 28.1% for Dongdaemun. Note that the number (and percentage) of Fist-day and Last-day visitors are compatible in each district. This reveals an intuitive fact that the number of overnight visitors who entered or left a district in a day tend to be balanced. This also demonstrates the robustness of the traveler segmentation algorithm.

The total number of visitors to districts does not seem to correlate with the relative balance of Full-day and Same-day visitors. This suggests that there exist other unobserved characteristics, rather than the districts' overall "popularity", that shape their abilities to attract

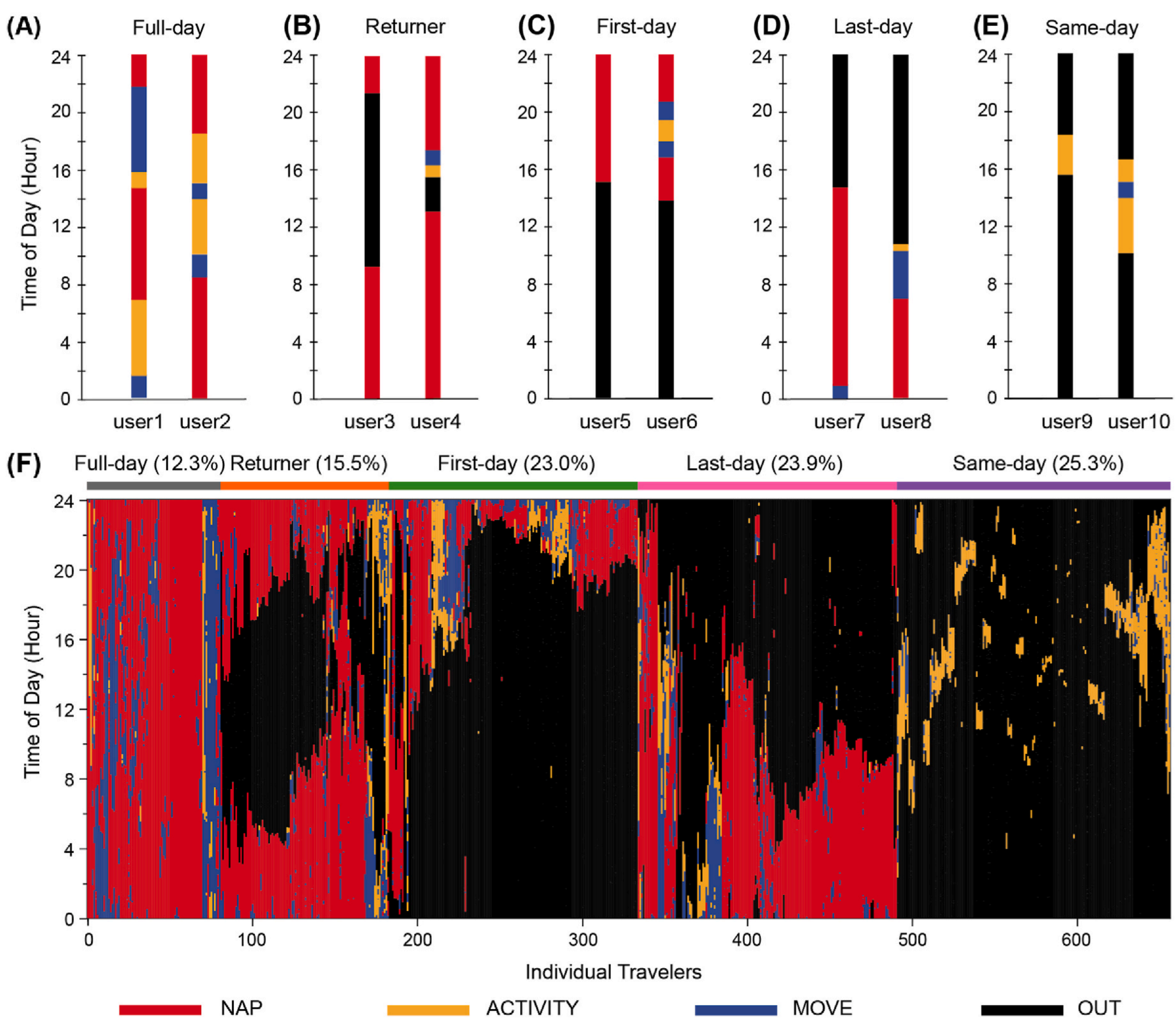

Fig. 3. (A–E) Examples of five types of travelers identified based on their daily activity sequence; (F) Results of traveler segmentation using district *Guro* on August 2, 2018, as an example.

Table 2
Composition of five types of travelers in each district (daily average).

ID	district	Full-day	Returner	First-day	Last-day	Same-day	Total
		No. (%)	No. (%)	No. (%)	No. (%)	No. (%)	No.
1	Jung	774 (8.6)	1537 (17)	1710 (18.9)	1858 (20.6)	3158 (34.9)	9037
2	Seodaemun	90 (2.5)	282 (7.9)	340 (9.6)	406 (11.4)	2432 (68.5)	3550
3	Jongno	99 (3.3)	264 (8.8)	284 (9.5)	317 (10.6)	2039 (67.9)	3003
4	Gangnam	334 (11.6)	313 (10.8)	427 (14.8)	472 (16.4)	1339 (46.4)	2885
5	Mapo	175 (6.1)	360 (12.5)	374 (13)	427 (14.8)	1540 (53.5)	2877
6	Yongsan	95 (5.3)	140 (7.8)	206 (11.5)	243 (13.5)	1114 (62)	1797
7	Gangseo	57 (4.4)	76 (5.9)	117 (9.1)	129 (10)	908 (70.6)	1286
8	Seocho	88 (7.7)	103 (9)	130 (11.4)	150 (13.2)	669 (58.7)	1140
9	Yeongdeungpo	97 (8.5)	135 (11.9)	158 (13.9)	179 (15.7)	567 (49.9)	1137
10	Songpa	76 (7)	55 (5.1)	84 (7.8)	93 (8.6)	774 (71.5)	1082
11	Guro	78 (12.1)	114 (17.6)	126 (19.5)	139 (21.5)	190 (29.4)	647
12	Dongdaemun	61 (11.3)	100 (18.5)	108 (20)	120 (22.2)	152 (28.1)	541

Note: ′%′ = No. of travelers in a given type/Total number of travelers who visited the district.

overnight vs. temporary visitors. To better understand the composition of travelers in these districts, we perform a simple clustering algorithm that categories them into three distinctive groups, as shown in Fig. 4. Group A contains Jung, Guro and Dongdaemun (Fig. 4A). The composition of travelers in these districts tend to be more balanced than ones in other groups. In particular, Group A tends to attract compatible amounts of Full-day visitors and Returners, and a higher number of Same-day visitors. Group B districts tend to attract more Same-day visitors (Fig. 4B), and Group C districts are dominated by Same-day visitors (Fig. 4C).

On top of the clustering results, we derive a simple metrics to reflect districts' abilities to attract overnight stayers. This traveler group is of particular interests to destinations and tourism stakeholders because they usually have much higher spending than same-day visitors. In our analysis, we add up the total percentage of Full-day visitors, Returners and First-day visitors as a composite indicator. The sum of these three groups yields a reasonable estimate of the total number of overnight stayers in a district in a given day. Note that Last-day visitors are not included in the formula because they represent visitors who "checked out" in a given day, therefore should not be double counted when First-day visitors ("checked in") are included. Given this definition, we present the percentage of overnight vs. same-day visitors in each district in Fig. 4E. The result clearly portrays the major difference among districts in attracting these two visitor groups. These characteristics could help

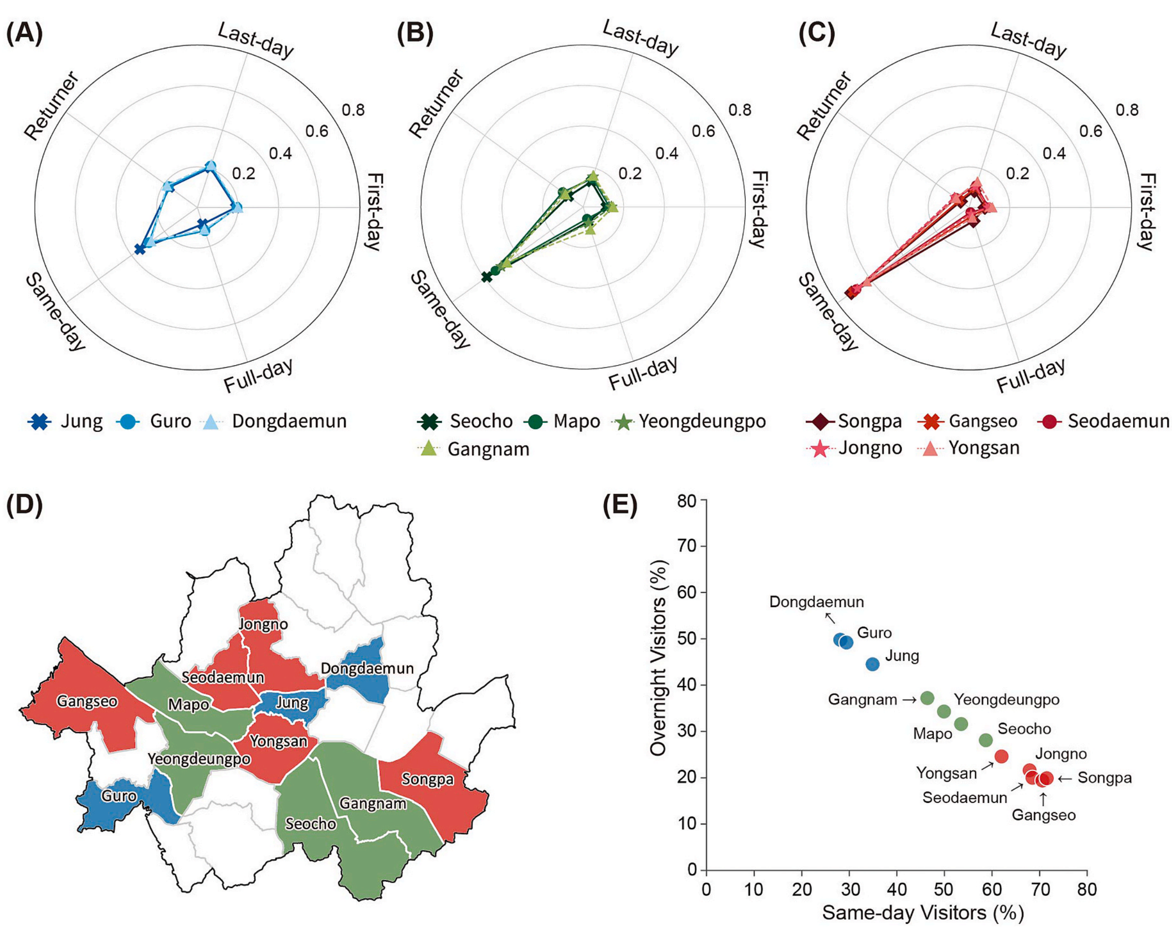

Fig. 4. (A–C) Three groups of districts based on their abilities to attract different types of visitors and their (D) spatial patterns; (E) The abilities of districts to attract same-day vs. overnight visitors.

decision makers better understand the roles districts play in attracting various types of travelers. The spatial patterns shown in Fig. 4D reflect the complementary roles districts play in attracting different types of visitors. Such insights could inform holistic tourism planning and marketing for the Seoul metropolis.

6.2. Temporal rhythms of same-day visitors

Compared to Full-day visitors, Same-day visitors stayed in a district temporarily. Given the variation of districts in their roles and characteristics, the way Same-day visitors used these districts could be different. Therefore, in this section, we further examine the temporal rhythms of Same-day visitors in districts by looking at when they arrived and left, and how long they tended to stay. Fig. 5 shows, on an average day, the percentage of Same-visitors entering (red line) or leaving (dash blue line) a district in each 1-h time window as well as the distribution of stay duration (box plot).

The results show varying dynamics of same-day visitors in the districts. Districts such as Jongno, Gangnam, Yongsan (Fig. 5A–C) were more attractive to Same-day visitors during the daytime. The incoming visitors peaked around noon time and the majority tended to leave the districts before evening. Except for the few who entered a district before sunrise, most of the visitors stay in these districts for less than 4 h. Comparatively, districts such as Songpa, Jung, Guro and Mapo (Fig. 5E–H) show a higher level of nighttime attractiveness. A notable fraction of Same-day visitors tended to leave these districts during the evening (e.g., after 9 p.m.).

A very special case is Gangseo (Fig. 5I). The curve of incoming visitors exhibits a few peaks with a few hours of gap, showing periodic attractiveness to the Same-day visitors, who usually remained in Gangseo for a very short time. As a district with the third largest airport (Gimpo international airport) in Korea, the observed temporal rhythm may partially be explained by the role of the district as a transportation hub. Likewise, for Seodaemun (Fig. 5D), most of the Same-day visitors stayed in the district less than an hour, producing an almost identical shape of curves for incoming/outgoing visitors. It clearly reflects the role of the district as a transfer stop for Same-day visitors.

The results in Fig. 5 suggest that Same-day visitors used districts in Seoul in different ways. The mobile big data allows for granular estimates of the attractiveness of districts and their variations over time. The observed temporal rhythms also empower decision makers to portray the "tourism signature" of the districts.

6.3. Districts as attractors/generators of visitors and their spatial interactions

In the previous subsection, we focus on analyzing the temporal rhythms of Same-day visitors within the districts. Another intriguing question is how these visitors contribute to the spatial interactions among different areas in Seoul. Intuitively, a Same-day visitor to a

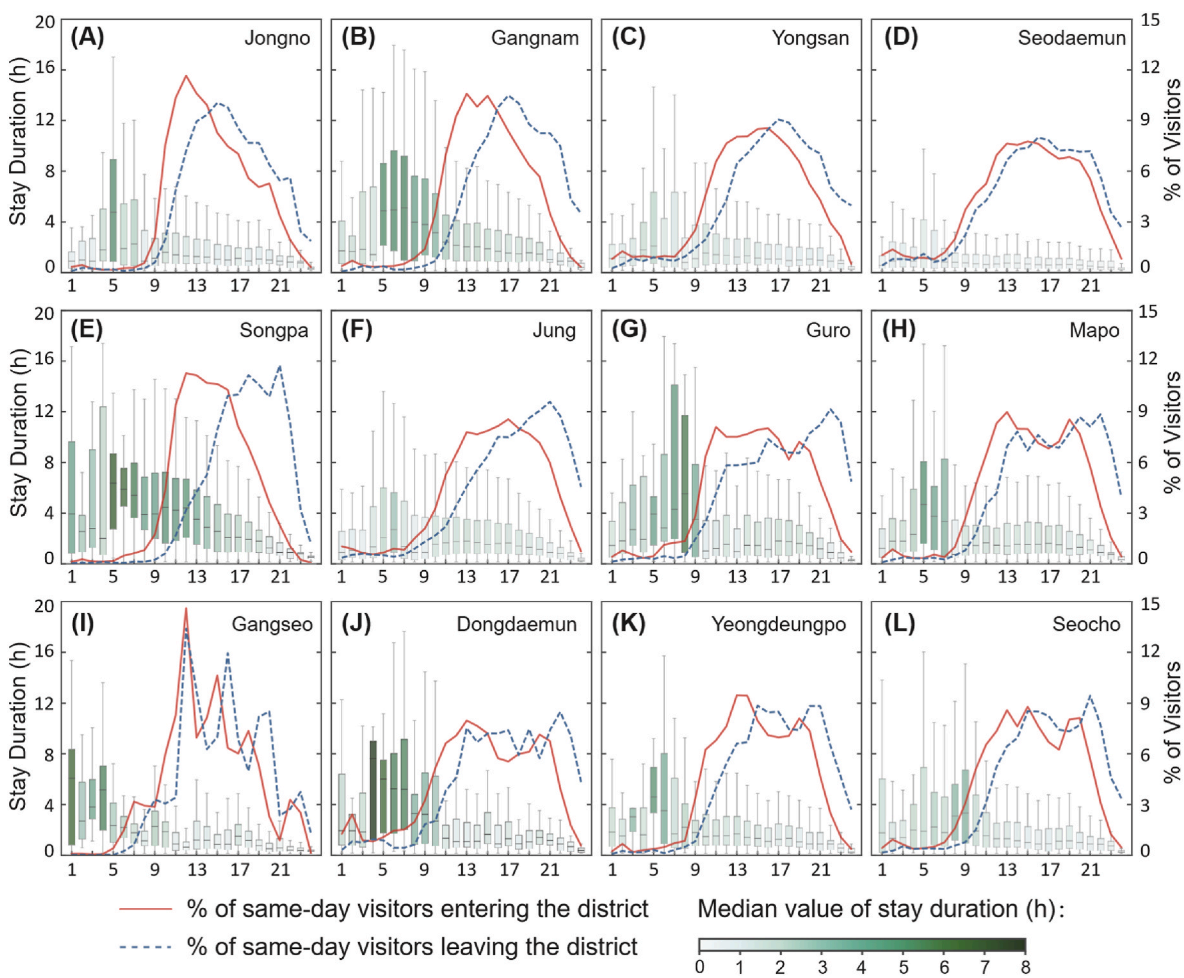

Fig. 5. Temporal rhythms of same-day visitors to each district. The red/blue lines show the percentage of same-day visitors that entered/left a given district during each 1-h time window. The box plot shows the distribution of stay duration for visitors entering the district during the given time window. All the statistics are derived based on the daily average during the study period. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

district in a given day must originate from another district where he/she resided. Therefore, relating the originating and target district(s) of these Same-day visitors would shed light on the functionality of districts and their spatial interactions.

The first question we examine here is — *Given the Same-day visitors to a district, where did they reside before paying the visits*? To answer this question, for a district in a day, we identify the Same-day visitors and locate their night-time anchor points (NAPs) in the previous day. Since these NAPs serve as a reasonable proxy of their dwell places, we can estimate, for each *target* district, the distribution of Same-day visitors by their originating districts. Fig. 6 shows the analysis results, using the top four districts by total number of visitors (Table 2) as an example. The width of the lines denotes the daily average number of Same-day visitors from each originating district. The color of each originating district denotes how much time on average the Same-day visitors tended to stay in the target district.

As shown in Fig. 6A, the Same-day visitors to Jung (1) district originated from a variety of other districts, with Seodaemun (2), Jongno (3) and Mapo (5) being the major contributors. From the perspective of stay duration, visitors from most of these originating districts stayed on average for two to three hours in Jung. The result becomes quite different as the target district switches to Seodaemun. As shown in Fig. 6B, most of the Same-day visitors to Seodaemun originated from Jung (1), and the duration of stay tended to be short. Jung also played the key role in contributing Same-day visitors to Jongno (3), as shown in Fig. 6C. Similar to Jung, Gangnam (4) as a target district was able to attract Same-day visitors from many other areas in Seoul (Fig. 6D). The results in Fig. 6 suggest that the abilities of a district in attracting Same-day visitors are uneven across geographic space. There is also a notable variation on how much time Same-day visitors tend to allocate given a specific combination of target-originating districts.

Similarly, we ask the second question — *Given the overnight stayers in a district who visited other areas in Seoul, where did their visit take place*? The results are shown in Fig. 7. Looking at Fig. 6 (A), based on the fact that large numbers of hotels are located in Jung, the district plays an important role of travel source that initiate for travelers visiting other destinations. Considering the motivations of international travelers, understanding culture and history of the destination can be one of key activities while they visit Korea. In this sense, since Seodaemun geographically close to Jung includes a popular historical museum, the travelers are likely to enjoy the historical activity before returning their accommodations (Fig. 7B). The similar finding can be observed in

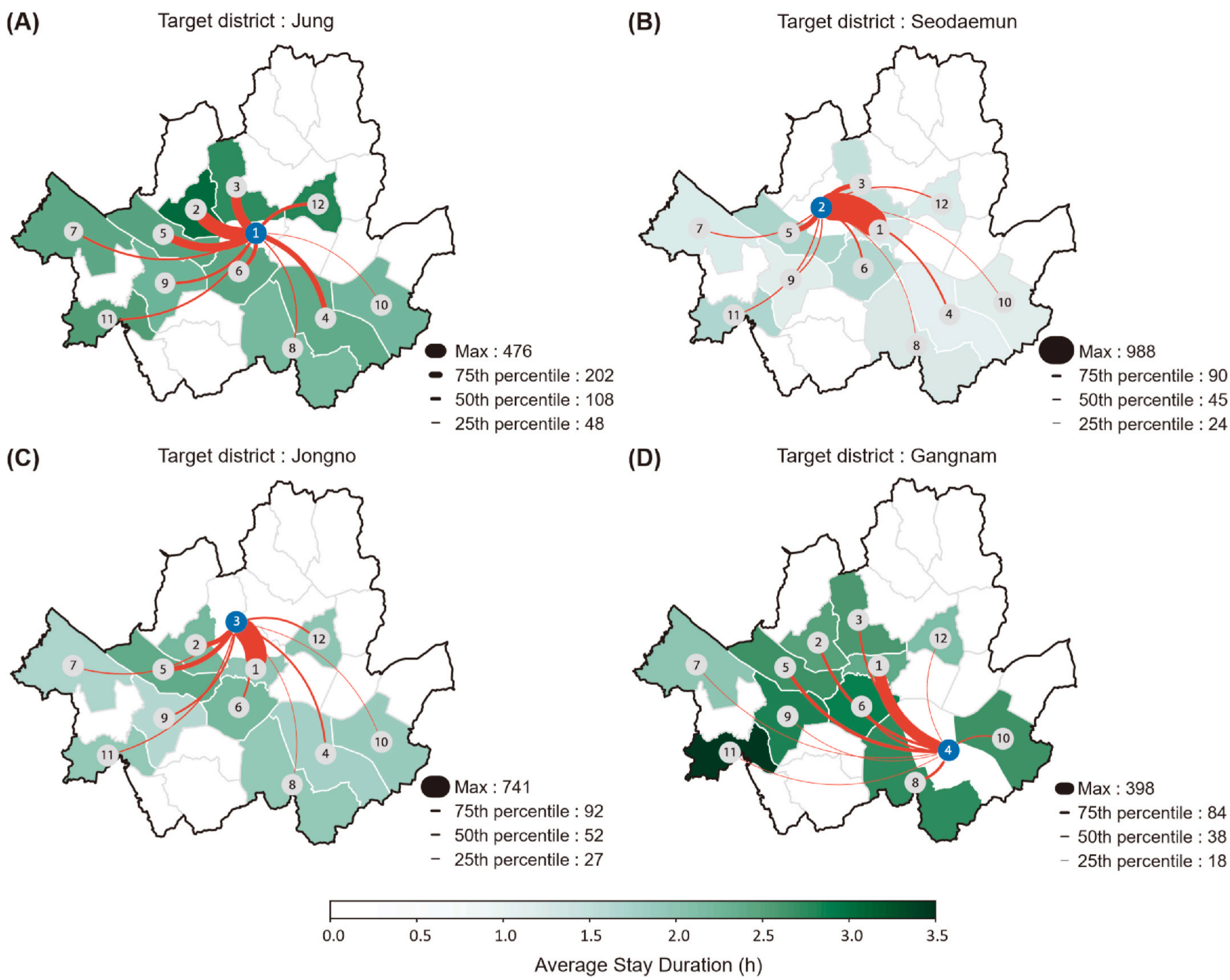

Fig. 6. Spatial distribution of the daily average number of Same-day visitors to a target district: (A) Jung; (B) Seodaemun; (C) Jongno; (D) Gangnam. The width of the lines denote number of Same-day visitors from each originating district, and the color denotes the average stay duration in the target district. The IDs of the districts can be referenced in Table 2. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

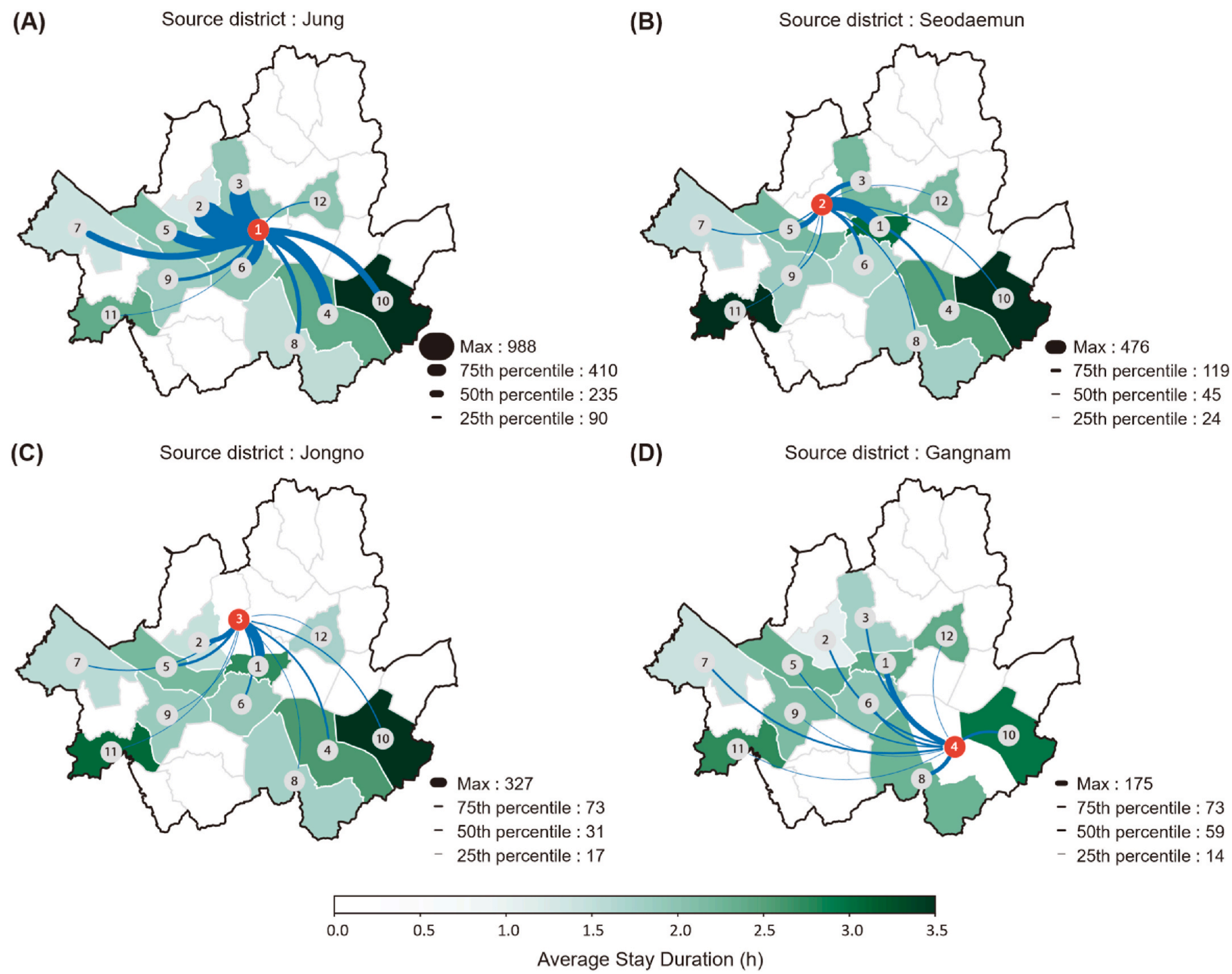

Fig. 7. Spatial distribution of the daily average number of Same-day visitors originated from a source district: (A) Jung; (B) Seodaemun; (C) Jongno; (D) Gangnam. The width of the lines denote number of Same-day visitors to each district, and the color denotes the average stay duration. The IDs of the districts can be referenced in Table 2. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

Jongno where a number of shopping and travel attractions are locations as well as it is an adjacent district with Jung (Fig. 7C). Relatively, Gangnam is located to south part of Han river as opposed to Jung at north part of Han river. Those travelers who leave Gangnam are more likely to be dispersed into diverse districts rather than linking to a specific district (Fig. 7D).

7. Conclusion and discussion

The characteristics of different cities attract various types of tourists (Dredge, 1999). Understanding the composition of tourists and the activity patterns of different types of intra-city tourists has profound importance for adapting urban tourism strategies in a targeted manner. The present study proposes a universal approach to classifying intra-city tourists, which not only caters to the development of geo-big data but also incorporates the perspective of urban tourism functions. Then, this research portrays the dynamic functions of the city destination and compares the differences between places by visualizing the activities of tourists within a city destination. Finally, this study quantifies the "overnight activity" interaction values between destinations to further understand the functional relationships between city destinations. This paper produces important academic and practical implications to tourism knowledge. Under the theme of data-driven segmentation, this research proposes an innovative approach to classifying travelers based on the sequences of travel activities from tourists. The existing literature has mostly explored travel distance as a criterion for segmenting travelers (McKercher, 2001; Nyaupane & Graefe, 2008). In this sense, this research analyzing mobile positioning big data suggests advanced method to classify travelers by understanding the type and composition of activities, which generates significant knowledge contributions to behavior-based segmentation in tourism.

In addition, this research also suggests the formation of functional interactions between city destinations according to the popularity of travel types based on tourist activity. It demonstrated the transfer of specific types of travelers between city destinations. This study empirically demonstrates the idea of formulating destination functions based on travel flow. C. Gunn (1997) introduced the concept of place design, and several researchers have highlighted the importance of functional design when planning destinations. The findings of this research suggest a means for revealing the regional functions of destinations by intra-travel flow and their functional structures by spatial interactions. The studies of (Beritelli et al., 2020; Park et al., 2020) have emphasized flow-based planning and management, suggesting the foundations of travel flow in destination design. However, to the authors' knowledge, this paper presents the first attempt to quantify the destination functions by applying travel movement patterns and integrating the place design concept with big data analytics. Built on the demand-driven view of destination planning conceptualizing destinations from travel flows (Beritelli et al., 2020; Reinhold, Laesser, & Beritelli, 2019), this study proposes a novel approach to characterizing destinations based upon the configuration of travel types (i.e., travel movement patterns). As opposed to the existing studies defining and planning the destinations based on attributes in the places (Battour, Ismail, & Battor, 2011; Litvin & Ling, 2001), this research suggests an alternative approach to uncovering the features of the destination from the structures of demand-driven (or flow-based) construct. This implication is related to the vision of smart tourism design relying on the capability of destinations to collect, curate, and analyze the enormous size of data and obtain insights from the big data to design operations, services and innovation (Xiang & Fesenmaier, 2017).

This research suggests a number of practical implications. The innovative segmentation method enables tourism marketers to identify different traveler types (e.g., full-day visitors; returners; same-day visitors) and how they organize activities throughout a day. The method can be used to complement or substitute traditional approaches (e.g., questionnaire) for segmenting travelers. Given the granular information revealed from the mobile phone data, destination marketing organizations (DMOs) are able to assess comprehensive and subtle movement patterns and to develop the data-driven segmentation. As opposed to traditional segmentation such as demographics, DMOs can construct behavior-based segmentation taking into consideration of temporal and spatial patterns as well as travel activities, and monitor the changes of segmentation structures. Thanks to the advancement of management information system, DMOs can develop the automation system facilitating for collecting and analyzing the mobility data of travelers and generating reports so that destination marketers instantly adopt the insights. As a result, tourism marketers can develop dynamic travel products connecting districts (or regions) with high spatial interactions according to different segments. Furthermore, the insights of sequential travel activities across different segmentation should be useful for DMOs to develop destination-based storytelling and thus enhance travel experiences. Moreover, understanding the functional interactions between city destinations (or districts in this study) is important for destination management and planners to arrange urban tourism resources from a macroscopic and holistic perspective. Specifically, the insights should be beneficial when destination marketing organizations recognize the functional images of their destinations and develop the travel products containing diverse values of regional functions, thereby ultimately improving destination competitiveness. Overall, this knowledge can contribute to the understanding of the relationship among tourism destinations, hotel management, the arrangement of tourism resources, and the sustainable development of tourism cities.

Finally, the findings of this study provide important implications during the COVID-19 era. The key purposes of this paper are to suggest an approach for classifying travel types based on activity patterns and characterizing regional functions at city destinations, which can be the foundation of destination designs (Park et al., 2020). Furthermore, travelers in the post-COVID-19 era are likely to present individual types of travel behavior and count on mobile technology to search for personalized destination information (Zheng, Mou, Zhang, Makkonen, & Yang, 2021). This means that travel activity patterns in post-COVID-19 should be more sophisticated and complex. Accordingly, the rich spatiotemporal information from mobile positioning data should be a critical source in destination management. More specifically, with the advancement of mobile technology, destination marketers have an opportunity to collect real-time mobility data of visitors. The segmentation method this study suggested can facilitate marketers to analyze the massive data and provide important insights into the dynamic changes of traveler types post-COVID-19. Destination organizations can effectively develop marketing strategies by observing changes in the roles and functions of the destinations accordingly.

This study essentially explored a specific type of tourism big data – mobile sensor data. It is suggested for future researchers to attempt the data integration approach to generating comprehensive data not only reflecting travel movement but also presenting consumption (e.g., transaction data), behavior (e.g., survey data), and experiences (e.g., consumer reviews). The inclusive data can facilitate tourism marketers and researchers to better understand travel decision-making process and behaviors.

Impact statement

The advancement of information technology enables tourism researchers to access big data such as mobile positioning data of travelers. Using Seoul as a study case, this research proposes an innovative approach to classifying travelers by the sequences of travel activity with individuals' trajectories. Recognizing the limitations on mobile sensor data, this research suggests for destination marketing organizations (DMOs) how to identify travelers' activities at the destinations and to segment travelers from the similarity of activity patterns. Tourism marketers can get a benefit to conduct a data-driven segmentation method rather than traditional (or a priori) segmentation approach. Furthermore, this paper attempts to characterize the functionality dynamics of city destinations associated to compositions of travel types. From destination planning perspective, the insights on functional interactions and structures comprising multiple city destinations can be foundation for DMOs to accomplish tourism destination design.

Credit author statement

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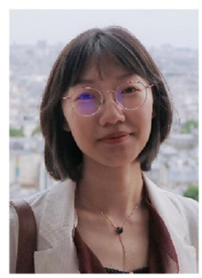

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