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# Coupling mobile positioning data and discrete choice model to decode travelers' spatial choices within urban destinations

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ABSTRACT

The growing availability of mobile positioning data offers new opportunities to understand onsite travel decisions, particularly how travelers organize activities spatially and the factors influencing these spatial choices. Coupling mobile positioning data of international travelers in three South Korean cities and extensive points-of-interest (POI) data, this study develops a discrete choice modeling framework to uncover the key factors that shape travelers' spatial choices. By introducing area-of-interest (AOI), a novel spatial unit that captures the cumulative effects of tourism resources and urban facilities, the study finds that travel distance to and volume of POIs in an AOI, as well as number of prior visits to the AOI during the same journey, are decisive factors with universal influence across the cities. We also identify factors with city-specific effects or varying influence with respect to travelers' nationalities and lengths of stay, providing insights for customized marketing and management strategies for the destinations.

## 1. Introduction

Upon arriving in a city, tourists often engage in multiple attractions and various activity locations in their travel itineraries (Caldeira & Kastenholz, 2018). Tourists select from a variety of city offerings and activities to plan itineraries that align with their expectations and desires (McKercher, 2004). Understanding the specific locales where tourists opt to engage in these activities can offer valuable insights into their interests, behavior, and mobility practices within urban destinations (Bauder & Freytag, 2015). These insights are valuable to governments and tourism sectors, guiding planning decisions, enhancing tourist experience, and fostering sustainable strategies (Edwards et al., 2010).

However, how tourists choose among various attractions and activity places in a city, a fundamental aspect of tourists' intra-urban behavior, is relatively understudied. Destination choice theories suggest that, due to scarce resources, tourists must make sacrifices when selecting destinations. Specifically, choosing a specific destination means forgoing others (Wong et al., 2017). Considering movements as an outcome of rational choices, a tourist is assumed to select the destination that maximizes the utility (Morley, 1994). Similarly, within a city, a tourist is spatially selective due to a limited time budget. They typically opt for places that align with their preferences and expectations, akin to consumers choosing desired products (Ben-Dalia et al., 2013). However, tourism research on spatial choices of tourists has primarily focused on the choice of destinations, such as countries and cities, often in the context of long-distance travel (Bursa, Mailer, & Axhausen, 2022a, 2022b). Tourists' spatial choices within cities, especially how they decide between different places, have received limited attention.

Discrete choice models are useful for analyzing spatial choices (Louvière & Timmermans, 1990; Eymann, 1995). In the tourism context, these models have been widely applied to investigate tourists' destination choices (Crouch & Louviere, 2000; Kemperman, 2021; Zhang & Jiang, 2021). Studies have utilized these models to determine how tourists evaluate competing destinations based on destination attributes (Pan et al., 2021), and how their evaluations differ based on personal characteristics (Liu et al., 2018; Masiero & Qiu, 2018). Insights from these studies can inform destination planning and marketing efforts by identifying the specific elements that can enhance destination attractiveness (Pan et al., 2021) and revealing the distinct interests of different

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tourist groups (Masiero & Nicolau, 2011). While these models offer a promising tool for analyzing spatial choices, most studies have primarily focused on examining how destination attributes affect tourists' selection of destinations. How tourists' spatial choices within destinations are affected by different factors remains poorly understood.

The factors influencing tourists' spatial choices in cities are multifaceted and complex (Caldeira & Kastenholz, 2020). Tourist experience within a destination is significantly affected by its attractions (Masiero & Hrankai, 2022). Despite this, extant literature has recognized several determinants of tourists' intra-urban behavior, such as distance (Lew & McKercher, 2006), transport connections (Hardy et al., 2020), attraction clusters (Jin et al., 2017), and accommodation locations (Shoval et al., 2011). Studies have predominantly focused on identifying factors contributing to tourist hotspot areas (e.g., Vu et al., 2015) or frequent movement patterns (e.g., Lau & McKercher, 2006). Tourists evaluate different places in the city based on these factors, leading to either visiting or skipping a specific place. However, these factors have not been incorporated into a holistic framework to assess their influence on spatial choices in cities. Additionally, existing studies are of a descriptive nature. The relative importance of these factors is not well understood.

Cities have distinctive spatial configurations, topographies, and transportation services, which can lead to variations in tourists' intra-urban behavior across cities (Lew & McKercher, 2006). The literature has indicated that tourists visit heritage sites more frequently in historic cities such as Vienna and Budapest (Kádár, 2014). In metropolitan cities such as New York (Hu et al., 2019) and Hong Kong (Zhou & Chen, 2021), tourists are more inclined towards areas featuring modern landscapes and cultural attractions. In this vein, an important question, whether tourists' spatial choices are affected in similar ways across cities, remains understudied. Addressing this question could provide critical insights into the uniqueness of urban destinations in shaping tourists' spatial decisions and the general patterns that may apply across cities.

The spatial preferences of tourists are often related to their sociodemographic characteristics (including gender, age, income and children in the family) (Chang, 2012; Curtale, 2018; Djeri et al., 2014), cultural backgrounds (Dejbakhsh et al., 2011), and trip characteristics (Shoval & Raveh, 2004). For instance, previous research has revealed that Asian and Western tourists are two contrasting groups that significantly differ in preferred activities, attractions, and areas in destinations (Dejbakhsh et al., 2011; Hofstede & Minkov, 1991; Mattila, 2000). Certain attraction clusters and movement patterns within a destination can also be distinguished by the length of stay in cities (Shoval & Raveh, 2004). This indicates that the influence and relative importance of the factors could vary across tourist groups based on their nationality and length of stay. However, this hypothesis has not been assessed thoroughly in a quantitative framework.

Tourist tracking technologies have significantly enriched empirical and theoretical tourism studies. Early survey-based studies demonstrated the predictability of tourist flows (Williams & Zelinsky, 1970) and identified distinct trip patterns and itinerary types (Mings & McHugh, 1992; Oppermann, 1995). The advent of GPS technology revealed the influence of accommodation on tourist behavior (Shoval et al., 2011) and distinct activity rhythms in tourist activities (Birenboim et al., 2013). Recent decades have seen mobile positioning data and geo-tagged social media, such as Twitter and Flickr, transforming tourism analysis by serving as proxies for mobility patterns of urban tourist activities (Kádár, 2014; Lansley & Longley, 2016). Notably, the growing literature on intra-urban tourism using big data and mobile tracking has provided new insights. Ahas and colleagues leveraged mobile phone data to explore domestic (Silm & Ahas, 2010) and foreign tourists' activities in Estonia (Nilbe et al., 2014). Vanhoof et al. (2017) identified and classified destinations by analyzing cell tower activity. Wang et al. (2021) employed social network analysis on cellular signaling data to examine tourism flow networks in Nanjing, highlighting structural differences between residents and non-local tourists. However, most studies either analyze mass population patterns using mobile data or individual behaviors with limited GPS coverage, lacking large-scale individual-level insights. Consequently, the factors and mechanisms influencing individual tourists' spatial choices within urban environments remain underexplored, limiting a comprehensive understanding of intra-urban tourism dynamics.

To address the research gaps, we develop a framework that integrates multi-source tourist big data and discrete choice modeling to analyze the influence of a range of factors on tourists' spatial choices in cities. We use international travelers in three major tourism cities (Seoul, Jeju, and Busan) in South Korea as our case study. Our contributions and aims are as follows.

- **Aim and motivation:** By leveraging travelers' mobile positioning data within cities, we aim to derive individual travelers' spatial choices from the activity locations in their traces. We introduce a novel spatial unit, area-of-interest (AOI), which considers the spatially clustered points-of-interest (POIs) in each city. This unit represents the competing places that travelers might visit. Our motivation is to model the spatial choices among the AOIs with a range of factors as explanatory variables, using the discrete choice modeling framework, thereby enhancing the understanding of urban travel behavior.
- **Hypothesis and analysis:** We hypothesize that various factors influence spatial choices differently across cities and traveler groups. To test this, we analyze the influence of these factors based on the model results, and further employ elasticity to quantitatively reflect the relative importance of each factor. The results could reveal the most important factors in determining the spatial choices in cities, and how sensitive the spatial choices are to the variation of each factor. This analysis aims to validate or reject the hypothesis regarding the universal or city-specific appeal of these factors.
- **Comparative analysis across cities:** We estimate different discrete choice models for the three cities and compare the influence and relative importance of these factors. The hypothesis is that while some factors have a universally appealing or repulsive effect, others exhibit city-specific influences. The analysis aims to confirm or refute this hypothesis, providing insights into the variability of spatial choices across different urban contexts.
- **Group-specific analysis:** Using the nationality information in mobile positioning data, we segment travelers into Asian and Western groups, and further divide them by their length of stay in the city. We establish separate models for these groups to identify the factors with generic and unique effects. Our hypothesis is that spatial choices vary across these groups, and our analysis aims to explore the variations quantitatively through cross-group comparison.

This study aims to contribute to a nuanced understanding of tourists' consumer behavior regarding their spatial decisions in the context of intra-urban travel. Insights from our empirical findings are intended to expand the knowledge of tourist behavior and, furthermore, inform urban tourism planning and management. Our methodology is designed to be transferred to other urban destinations and extendable to more sophisticated choice analyses.

## 2. Literature review

### 2.1. Tourist movements within urban destinations

Tourist movements in cities involve location changes, particularly from accommodation to attractions or between attractions (Xia & Arrowsmith, 2005), to engage in and shift between activities (Bieger & Laesser, 2004). In the past decade, the advent of mobility big data, generated by personal mobile devices (Gonzalez et al., 2008) and positioning technologies (Edwards et al., 2010), has advanced human mobility research. Mobility big data of tourists, recording their detailed footprints and traces, has enabled researchers to gain insights into

tourists' activity places (Zoltan & McKercher, 2015), spatial extents (Zakrisson & Zillinger, 2012), and transport usages (Caldeira & Kastenholz, 2018) within cities. The data permits aggregate-level analysis based on the footprints of mass tourists, such as revealing hotspot areas (Mou et al., 2020). Tourist flows between hotspot areas can be modeled as a mobility network, providing insights into the structural properties of the urban tourism system (Park, Kim, et al., 2021).

Studies have pinpointed various factors that influence tourist intra-urban movements. Distance, including the distance between activity locations (Jin et al., 2018) and the relative distance from accommodation to activity locations (Shoval et al., 2011), restrains tourist movement range in cities. Conversely, major attractions play a prominent role in pulling tourists (Jin et al., 2017; Masiero & Hrankai, 2022). Concentrated zones of specific resources, like shopping districts, are often marketed as attractions (Pearce, 1998). Tourists weigh the attractiveness of attractions against the availability of transport links to decide their movements (Hardy et al., 2020). However, how tourists' spatial choices in cities are affected by various factors has not yet been examined in a holistic framework. It is not clear what factors play the most important role in determining spatial choices.

Tourist movement patterns are often related to their personal attributes and vary based on the city. Tourists with different nationalities (Han et al., 2018), cultural backgrounds (Dejbakhsh et al., 2011) or genders (Chang, 2012) have distinct movement ranges (Dejbakhsh et al., 2011), preferences for certain attractions (Vu et al., 2015) and activity places (Han et al., 2018). Moreover, tourists with short and long stays are also found to differ in their movement styles (McKercher & Lau, 2008), preferred activity locations (Xu, Xue, et al., 2021), and travel distance (Shoval & Raveh, 2004). This is because travel plans must be organized within the constraints of limited time and space (i.e. space-time tension) (Hägerstrand, 1970, pp. 143–158; Huang & Wu, 2012). As a result, tourists value the related factors differently according to different amounts of time budget. On the other hand, the way a city organizes its desired attractions and facilities can affect how tourists move within the urban space (Edwards & Griffin, 2013). Local transportation networks and city topography also shape tourist intra-urban movements (Lew & McKercher, 2006), thus resulting in distinctive behavior patterns in cities.

People's movement stems from the spatial decision-making of individuals (Lloyd, 1997). Individual tourists select among various activities to decide their preferred movements (McKercher, 2004). This aspect pertains to how various elements and offerings of a particular place attract or disinterest tourists in the city. This information is valuable to local tourism industries for integrating tourist needs and preferences into tourism products (Ben-Dalia et al., 2013). However, existing studies on tourists' intra-urban movements are primarily descriptive. Our understanding of how tourists decide among the competing places in cities, and how different factors influence their spatial decisions, remains limited.

### 2.2. Tourist spatial choice: perspectives and modeling

Spatial choices refer to the decisions travelers make about their locations and movements in space. From a microeconomic perspective, empirical analysis of spatial choices is equivalent to the analysis of consumer demand for location-specific products (Eymann, 1995). In the tourism context, these location-specific products typically include destinations (e.g., Pan et al., 2021), accommodations (e.g., Wang et al., 2020), attractions (e.g., Bauder & Freytag, 2015; Zheng et al., 2017), and means of transportation (Bursa, 2024), which is playing a crucial role in facilitating both long-distance travel to destinations, and local trips within them (Bursa et al., 2022a, 2022b; Miravet et al., 2021). At the macro-scale, tourist movements typically involve inter-destination travel, i.e., travel from the place of residency to a destination (Bieger & Laesser, 2004), or between destinations (Dejbakhsh et al., 2011). At the micro-scale, the movements include intra-destination or intra-attraction travel, such as moving from accommodation to an activity location (e.g., an attraction) or between activity locations at a destination (Dejbakhsh et al., 2011), and the continuous movements within an attraction (Xia et al., 2011). Accordingly, spatial choice at the macro-scale is primarily about destination choice, while at the micro-scale, it involves the selection of activity locations at a destination and the routes for engaging with the attraction environment.

Spatial choices at the macro-scale, i.e., destination choices, have been a key area in tourism research (Bursa et al., 2022a, 2022b). Tourism destinations usually refer to well-defined geographical areas such as countries or cities (Buhalis, 2000). Tourist destination choice can be conceptualized as a consumer decision to purchase tourism products (Wahab et al., 1976). Tourists are expected to seek an intangible return from such purchase behavior (Wahab et al., 1976). However, limited efforts have been devoted to examining whether such consumer behavior can effectively explain spatial choices within cities.

Discrete choice models, derived from random utility theory (Thurstone, 1927), have been widely applied to analyze destination choice (Kemperman, 2021). These models posit that individuals make choices that maximize their utility (Morley, 1992, 1994). The models have enabled researchers to investigate how tourists value different destination attributes (Pan et al., 2021), and how their valuations vary based on their personal and psychographic characteristics (Liu et al., 2018). Discrete choice model classes allow for the correlation of choices or alternatives, and the variation of preferences among individuals (Train, 2009). Such flexibility permits researchers to align modeling with specific behavior assumptions such as heterogeneous preferences (Masiero & Qiu, 2018).

While discrete choice models represent a promising approach to analyzing spatial choice, it is challenging to apply them to the specifics of intra-urban travel. First, data documenting tourists' travel-related decisions within destinations is limited (Bursa et al., 2022a, 2022b). Second, discrete choice modeling requires mutually exclusive alternatives that represent the bundles of location-specific products offered at distinct places (Eymann, 1995), which is called ***the choice set***. Given the virtually unlimited number of places tourists can visit in a destination (McKercher & Lau, 2008), it is challenging to effectively define such alternatives to represent all the possible places, i.e., ***the universal choice set***. Since individuals have a limited capacity for storing and processing information, the large number of alternatives are usually mentally portioned into different subsets of choices, i.e., ***awareness choice set***. Assumptions on available spatial options, i.e., ***consideration set***, generated from groupings or aggregations of spatial elements, must be made (Ben-Akiva & Bierlaire, 1999; Haynes & Fotheringham, 1990).

## 3. Methodology

### 3.1. Study area

Three top urban destinations for international travelers visiting South Korea are selected as our case study (Fig. 1). Seoul is the capital and the most popular tourism destination in the country, attracting over 12 million international travelers annually from 2015 to 2019 (Seoul Tourism Organization, 2020). Jeju is a volcanic island off the southern coast of South Korea. It has abundant natural attractions, historical sites, and resort places, predominantly distributed along its coastal area. Jeju attracted more than 1.2 million overseas travelers in 2018 (Jeju Special Self-Governing Province, 2020). Busan, the country's second-largest city, is an important manufacturing and transportation hub. Over 2.4 million international travelers visited the city in 2018 (Busan Metropolitan City, 2019).

### 3.2. Mobile positioning data and POI check-ins

We utilize mobile positioning data collected from 83,978 international travelers to the three cities during the period from Aug 1, 2018, to

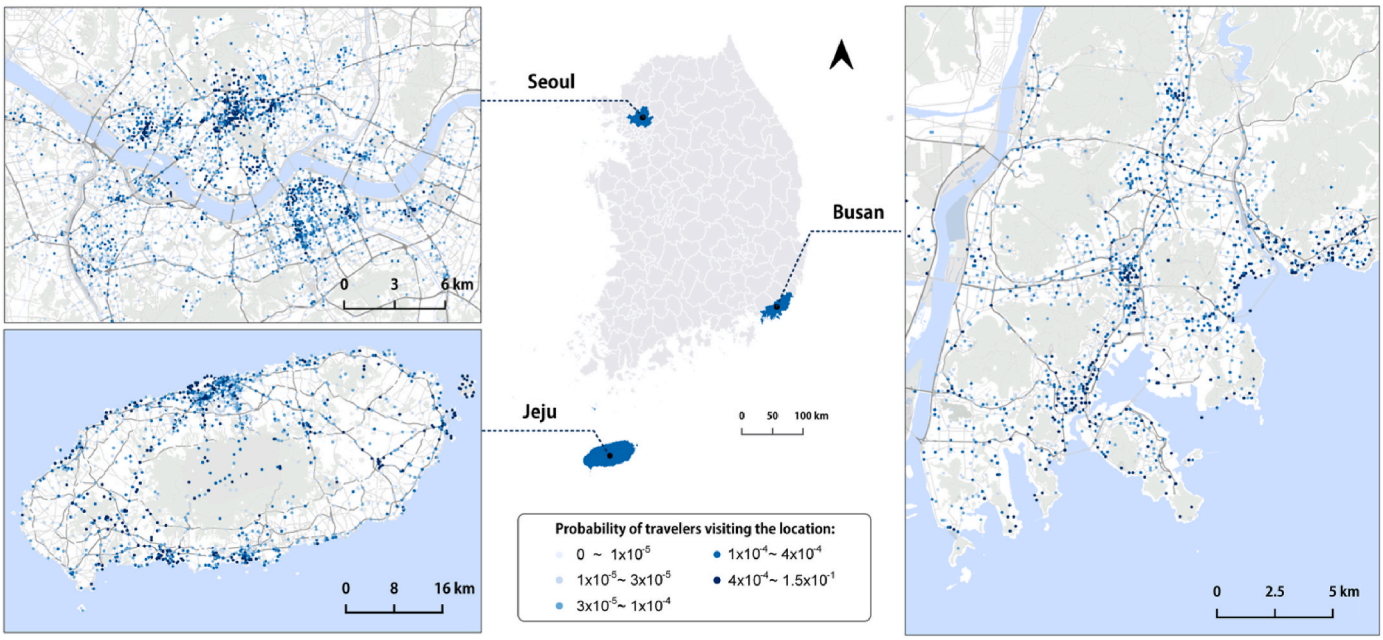


**Fig. 1.** Study area of this research: Seoul, Jeju, and Busan. The probability of travelers visiting different cellphone tower locations within these cities, derived from mobile positioning data.

Aug 15, 2018. Table 1 exemplifies the data records of a traveler. Each record indicates a traveler's stopover at a location (at a cellphone tower level), containing a unique and anonymized user ID, the traveler's nationality (e.g., Spain), the start time and end time of the stopover, and the coordinates of the location. The time-ordered sequence of the records represents the traveler's sequential trips between locations. Despite this anonymization, the user IDs allow for tracking each individual's trajectories during the entire stay in the destination city. It is noteworthy that the spatial granularity of the data depends on the cellphone tower density. The average distance of a cellphone tower to its closest tower is 152m in Seoul, 156m in Jeju, and 110m in Busan. Such density ensures fine-grained observations of travelers' footprints.

This study collects Foursquare check-in data of over 200,000 points-of-interest (POIs) in the cities. Foursquare is a location information provider and a popular location-based platform that allows users to broadcast the places they visit through check-ins. The POI check-in data contains geographical coordinates, including latitude and longitude, and each POI's category, such as museum and hotel. These POIs offer comprehensive and enriched information about the specific facilities, venues, and amenities that travelers might visit or be interested in. We utilize the location and category information of the POIs to detect and characterize the AOIs in the cities.

To explore how the influence of different factors varies with travelers' nationalities and lengths of stay in the cities, we segment the travelers into several groups to estimate parameters for separate discrete choice models. To ensure sufficient choice samples for each group, the travelers are aggregated into Asian and Western groups (Fig. 2a). On the other hand, most travelers stayed in the cities for less than 6 days. The average length of stay in Seoul, Jeju, and Busan is 3.16, 3.36 and 2.68 days, respectively (Fig. 2b). We further divide travelers based on the length of stay: below average (2–3 days), above average (4–5 days), and significantly longer ($\geq$ 6 days). To exclude possible transit passengers, all one-day travelers are removed. Table 2 shows the number of travelers in each group.

**Table 1**
Examples of a traveler's mobile positioning records.

| User ID | Nationality | Start Time | End Time | Tower ID | Tower Coordinates |
|---|---|---|---|---|---|
| 41***16 | *** | 2018/08/14 23:43:01 | 2018/08/15 05:53:34 | 23 | 126.2***, 37.5*** |
| 41***16 | *** | 2018/08/15 06:12:43 | 2018/08/15 09:33:54 | 11 | 126.6***, 37.3*** |
| 41***16 | *** | 2018/08/15 10:55:45 | 2018/08/15 17:43:56 | 53 | 126.1***, 37.2*** |
| 41***16 | *** | 2018/08/15 18:43:01 | 2018/08/16 05:54:46 | 23 | 126.2***, 37.5*** |

### 3.3. Derive traveler trips from mobile positioning data

This study derives the trips of travelers between their meaningful activity locations from the mobile phone data. However, the signal of a mobile device could oscillate between neighboring cellphone towers and, thus, may indicate some meaningless activity locations and deceptive trips (Xu, Li, et al., 2021). To resolve this, we adopt the concept of *activity anchor point* (Dijst, 1999), defined as the location where a traveler stayed for a significant amount of time, to capture the meaningful activity location. Extracting the sequence of activity anchor points for each traveler can reduce deceptive trips. To this end, this study adopts the method developed by Xu et al. (2020).

Given the time-ordered sequence of a traveler's mobile positioning records (Fig. 3a), the method follows an aggregation process. First, the location with the longest total stay duration is selected as an aggregation center. Second, records within a distance threshold ($\Delta d$) of the center are aggregated to the center. For unprocessed records, the process is repeated until all records are aggregated. The locations in the resulting trace are the activity anchor points (e.g., $r_1$-$r_3$ in Fig. 3b). The movement between two sequential stays (e.g., $A$ to $B$ in Fig. 3b) in the activity anchor points can thus well represent a meaningful trip. Considering the cellphone tower density in our data, $\Delta d$ is set to 500m.

We exclude travelers' trips to their accommodation locations during the day, as accommodation choice is often a part of pre-journey decision-making. To identify each traveler's accommodation locations, we extract the activity anchor points where a traveler stayed for more than 3 h between 00:00 a.m. and 07:00 a.m. (e.g., $A$ in Fig. 3b). These points can effectively represent individuals' overnight locations (Xu et al., 2020).

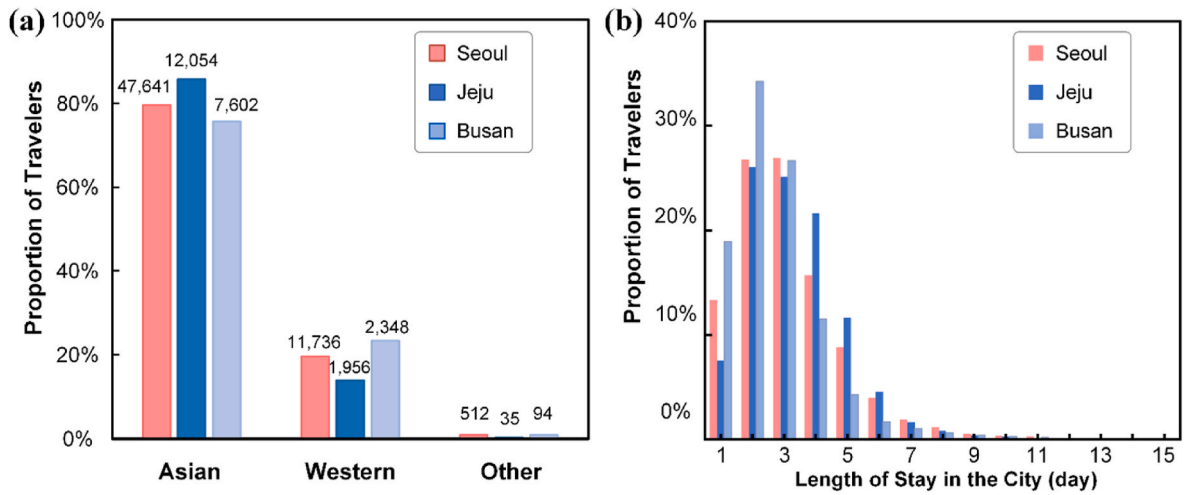


**Fig. 2.** The proportion of travelers with different (a) nationalities and (b) length of stay in the cities.

**Table 2**
Number of travelers in each group.

| Nationality | Asian | | | Western | | |
|---|---|---|---|---|---|---|
| Length of Stay (day) | 2–3 | 4–5 | ≥ 6 | 2–3 | 4–5 | ≥ 6 |
| Seoul | 25,659 | 12,302 | 3,820 | 6,218 | 2,268 | 1,229 |
| Jeju | 6,061 | 4,151 | 987 | 1,105 | 513 | 140 |
| Busan | 4,755 | 1,178 | 249 | 1,322 | 380 | 185 |

### 3.4. Detect areas-of-interest (AOIs)

This study introduces *areas-of-interest* (AOIs) to represent the places travelers might visit. An AOI is a multi-functional area represented by spatially aggregated POIs (Mou et al., 2020). AOIs can capture the irregular spatial extents of the clusters of attractions, venues, and amenities (Vu et al., 2015). In this study, we utilize AOIs within a city as the alternatives for spatial choices. Our rationale is that, first, a traveler's decision to visit a place is affected not only by a specific location (e.g., an attraction) but also by its surrounding environment (e.g., the number of nearby restaurants).Second, AOIs can aggregate numerous activity locations, ensuring a tractable choice set for modeling.

To detect the AOIs within a city, this study introduces a hierarchical DBSCAN clustering method using the POIs of the check-in data. The method aims to improve the naive DBSCAN clustering with a fixed distance threshold, which may ignore the areas with sparse POIs and cannot well split two adjacent AOIs (Chen et al., 2019). Fig. 4a illustrates the proposed method. Using an area threshold $\delta a$ to limit the AOI size, the method iteratively performs DBSCAN clustering with a distance

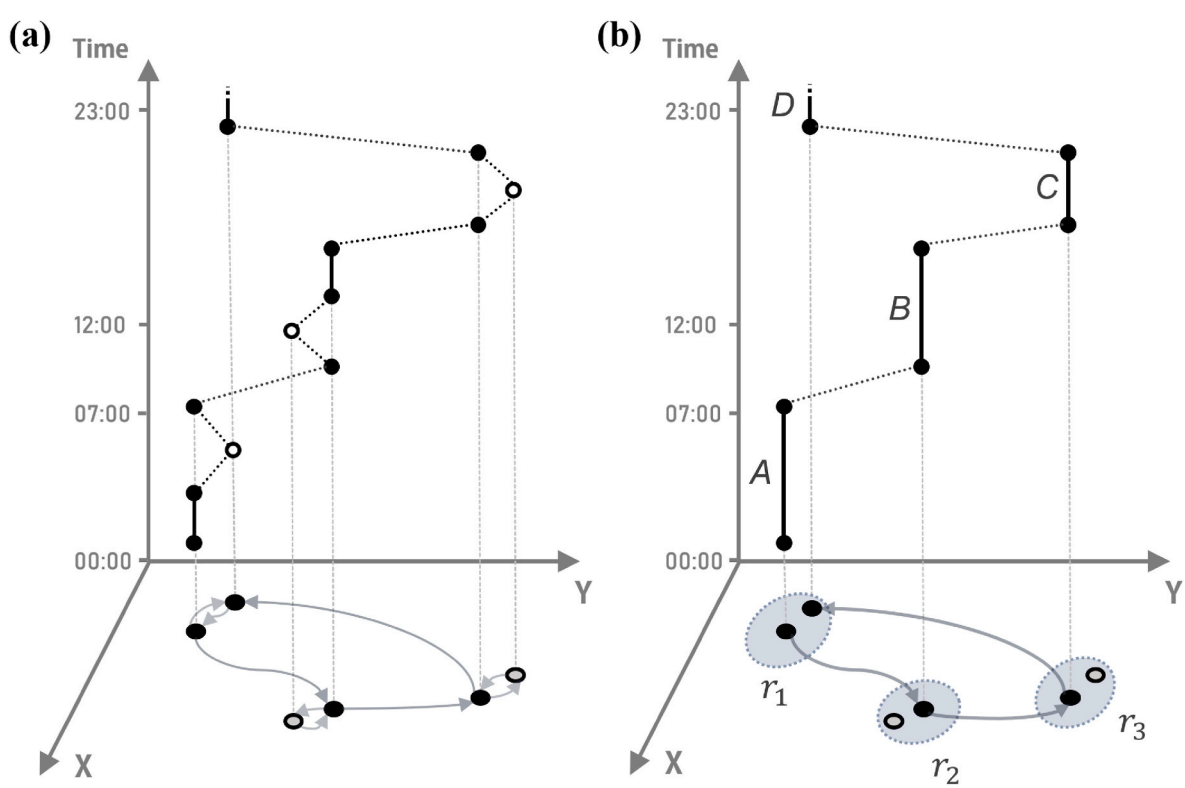


**Fig. 3.** (a) A traveler's trace between different cellphone towers in mobile positioning data. (b) The extracted activity anchor points, $r_1$, $r_2$ and $r_3$, and the sequential stays, *A-D*.

threshold ($\delta d$) based on the POIs. At the end of each iteration, clusters with area size smaller than $\delta a$ are identified as AOIs. All associated POIs of the identified AOIs are removed, and the $\delta d$ is slightly reduced for the next iteration. The iterations repeat until all POIs are clustered into AOIs.

A traveler's trip from his/her current AOI to the next is considered as a choice sample. To this end, travelers' trips are converted from cellphone-tower-level to AOI-level. The start and end locations (i.e., activity anchor points) of each trip are assigned to the AOIs they fall within, or to the nearest AOI if outside any AOI. We exclude the trips that happened within AOIs, as they might represent the intra-attraction movements. However, this may cause information loss. A greater $\delta a$ would result in fewer but larger AOIs, leading to more trips being excluded. A smaller $\delta a$ would generate more AOIs but may result in a large and intractable choice set. We set $\delta a$ at 2 km$^2$, corresponding to a reasonable walking distance of approximately 800 m, as supported by transport studies of both Eastern and Western countries (Jiang et al., 2012; Ryan et al., 2016). This choice preserves most trips while maintaining a manageable choice set. Consequently, we identified 666 AOIs in Seoul, 408 in Jeju, and 455 in Busan, with less than 10 % of the trips excluded (9.56 % in Seoul, 5.66 % in Busan and 2.53 % in Jeju).

To validate whether these POI clusters accurately reflect the spatial patterns of tourist activities, we conducted a kernel density analysis (using total length of stay as weight) on the mobile phone dataset, which represents tourists' actual movements. The resulting activity heatmap closely aligns with the identified AOIs in size, location, and geometric shape, confirming that the AOIs effectively represent tourist spatial choice sets across the three destinations (as shown in Fig. 5).

### 3.5. Development of discrete choice models

We utilize discrete choice models to examine the influence and relative importance of different factors. A traveler is assumed to choose the AOI that can maximize his/her utility. The utility for a traveler $i$ to choose an AOI $j \in I$ can be formulated by a linear-form function:

$$U_j^i = V_j^i + \epsilon_{ij} = \sum_k \beta_k x_{j,k}^i + \epsilon_{ij} \tag{1}$$

where $V_j^i$ is the observed portion of utility that can be captured by the explanatory variables. $\epsilon_{ij}$ is a random residual, which stands for the unobserved portion of utility. $x_{j,k}^i$ is an explanatory variable. $\beta_k$ is the model coefficient, representing the marginal (dis)utility of the variable.

In this study, the choice probability is approached by *multinomial logit* (MNL) models. The probability for traveler $i$ to choose AOI $j$ is formulated as:

$$p_i(j) = \frac{\exp\left(V_j^i\right)}{\sum_{h \in I} \exp\left(V_h^i\right)} \tag{2}$$

The MNL model, while widely used, is often criticized for its reliance on the Independence of Irrelevant Alternatives (IIA) assumption, which may yield biased estimates if alternatives are correlated (Ben-Akiva & Lerman, 1985). Mixed logit models address this limitation by accommodating unobserved heterogeneity through random parameter distributions, offering greater flexibility. However, our analysis confirms that the IIA property holds for most AOIs in this study (see Section 4.1), validating the suitability of MNL for our context. To further corroborate this choice, we compared mixed logit and MNL outputs on a subsample. Both models yielded statistically similar behavioral interpretations, but mixed logit required significantly greater computational resources and time (see Appendix), particularly due to the challenges of testing distributional assumptions for large choice sets. Given these trade-offs, we prioritize the MNL framework for its computational efficiency, and interpretability. This approach ensures clarity without compromising the robustness of findings.

Given the substantial heterogeneity in choice sets and contextual factors across cities, including socio-economic attributes, built environments, and traveler decision-making dynamics, one unified model integrating all three regions would risk conflating distinct behavioral mechanisms. Therefore, we opted to use separate models for each city rather than integrating them into a single framework. While separate models limit direct parameter comparison across cities, we address this by using *elasticity* measures to quantify the relative importance of factors within each city. *Elasticity*, defined as the percentage change in the probability of choosing an alternative in response to a one-percent change in a variable (Ben-Akiva & Lerman, 1985), serves as a unitless indicator reflecting the sensitivity of choices to variations in explanatory variables (Train, 2009). We employ the probability-weighted sample enumeration method (Ben-Akiva & Lerman, 1985) to calculate the elasticity of each variable, facilitating model comparison across the three cities.

This study incorporates three kinds of explanatory variables (Table 3).

1) *Distance* between activity locations and between accommodation location and activity location has a profound influence on tourist movements (Lew & McKercher, 2006; McKercher & Lau, 2008). For each AOI, we measure the distance from the traveler's current location to the AOI, and the distance for returning to his/her accommodation location from the AOI.

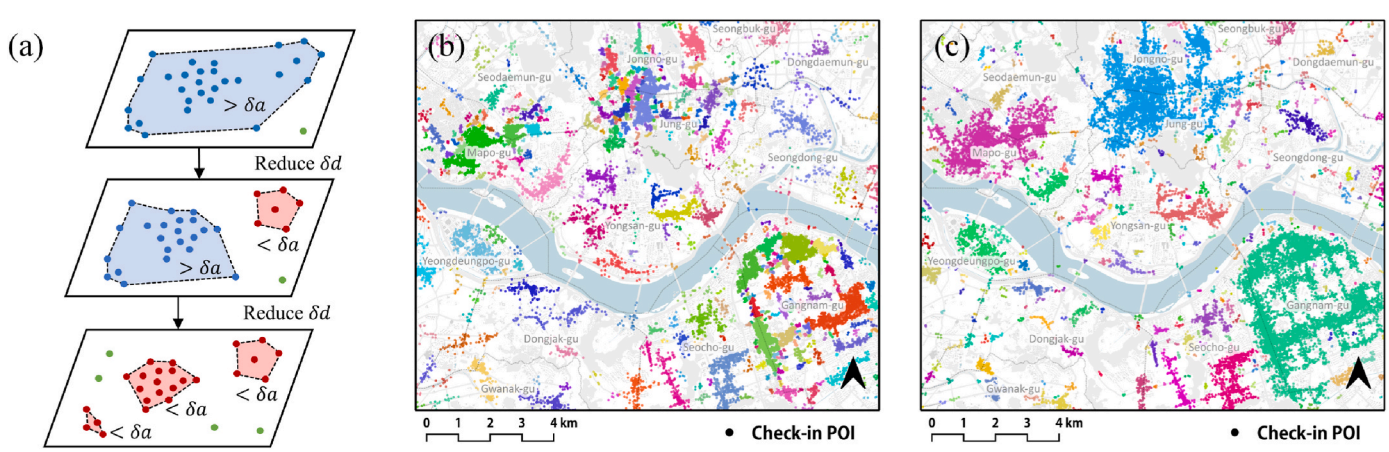


**Fig. 4.** (a) The illustration of the hierarchical DBSCAN clustering method; (b) AOIs identified in the major area in Seoul by the proposed method with $\delta a = 2km^2$; (c) AOI results by traditional DBSCAN with $\delta d = 500m$.

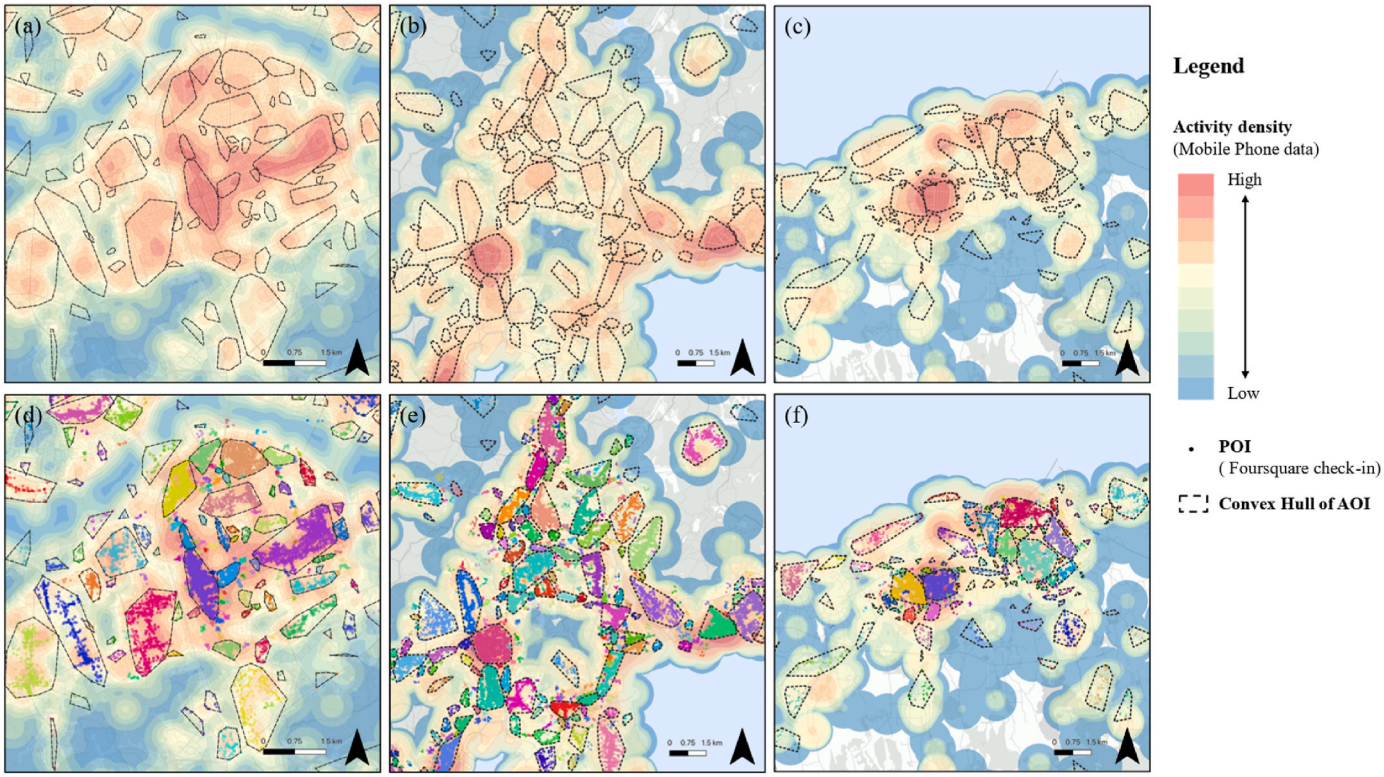


**Fig. 5.** Comparison of tourist activity intensity derived from the mobile phone data with the identified AOIs in: (a) Seoul, (b) Busan and (c) Jeju. Sub-figures (d–f) denote the same areas by overlaying Point-of-Interests (POIs) that are used to derive the AOIs.

**Table 3**
Explanatory variables.

| | Explanatory Variable |
|---|---|
| *Distance* | Distance to the AOI |
| | Distance from the AOI to the traveler's accommodation location* |
| *Functional characteristics* | Number of POIs (log10) in the AOI |
| | Proportion of POIs in the following categories: 1) Amusement/entertainment attraction; 2) Natural attraction; 3) Heritage attraction; 4) Recreational attraction; 5) Public transportation; 6) Accommodation; 7) Restaurant*; 8) Retail; 9) Nightlife; 10) Public service; 11) Education and health; 12) Other POIs** |
| *Revisitation* | Number of prior visits to the AOI during the current journey |

Note: *: excluded from the models due to high multicollinearity; **: include bank, and personal services, residential buildings, and recreational facilities.

2) *Functional characteristics* of the urban environment are an important dimension in understanding the leisure function of urban destinations (Jansen-Verbeke, 1986). For each AOI, we measure the total number of POIs (log10) to reflect the quantity of potential activity locations. To capture the elements and city offerings of each AOI that may attract or deter tourists, we measure the relative amount (proportion) of 12 categories of POIs in the AOI, including four types of attraction (Westcott & Anderson, 2021) and eight common types of facility.
3) *Revisitation* reflects tourists' loyalty and regular travel behavior (Oppermann, 2016). For each AOI, we calculate the number of prior visits of the traveler to the AOI during his/her entire stay within the city.

However, to address multicollinearity among the variables, we conducted a Variance Inflation Factor (VIF) analysis. To ensure that all VIF values were below the commonly accepted threshold of 10, we removed two variables from the models: the distance to the accommodation location and the proportion of restaurant POI.

## 4. Result

### 4.1. Model results for Seoul

We performed the IIA property test following the Small and Hsiao test approach (Small and Hsiao, 1985). The results suggest that the IIA property holds with most of the identified AOIs in the three destinations (658/666 in Seoul, 450/455 in Busan, 399/408 in Jeju). Therefore, the model's IIA assumptions are valid for the majority of the AOIs analyzed, empirically supporting the adequacy of MNL for the study. In addition, to empirically validate the robustness of the MNL framework, we performed a comparative analysis between mixed logit and MNL models using a subsample of the Seoul dataset (19,785 observations, ~5.7 % of the full sample). In this experiment, we assumed random parameter distributions (specifically, normal distributions for heterogeneity testing) to align with conventional mixed logit specifications. Despite the mixed logit model's theoretical capacity to capture unobserved heterogeneity, its results exhibited negligible divergence from MNL in terms of behavioral coefficient significance and directional interpretation (see Table A.1 in Appendix). Given the computational demands of mixed logit, particularly for large-scale choice sets requiring iterative distribution testing, alongside its marginal explanatory gains, these results empirically justify the use of MNL as the primary methodological framework.

Table 4 shows the MNL model results for travelers in Seoul. The models have a pseudo-$r^2$ of 0.27–0.33 and outperform null models in terms of log-likelihood, showing a good goodness-of-fit. As suggested by Domencich and McFadden (1975), a pseudo-$r^2$ of 0.2–0.4 is comparable with a value of $r^2$ between 0.7 and 0.9 of an ordinary linear regression.

Most coefficients significantly differ from zeros at the 1 % or 5 % level, demonstrating that these factors do have an influence on the

**Table 4**
MNL model results for travelers in Seoul.

| Nationality | Asian | | | Western | | |
|---|---|---|---|---|---|---|
| Length of stay (day) | 2–3 | 4–5 | ≥ 6 | 2–3 | 4–5 | ≥ 6 |
| | coef. | coef. | coef. | coef. | coef. | coef. |
| *Distance* | | | | | | |
| Distance to the AOI | −0.298*** | −0.318*** | −0.336*** | −0.334*** | −0.327*** | −0.329*** |
| *Functional characteristic* | | | | | | |
| Num. of POIs (log10) | 0.798*** | 0.806*** | 0.825*** | 0.728*** | 0.735*** | 0.766*** |
| Heritage attraction (%) | 3.530*** | 3.688*** | 3.359*** | 3.346*** | 3.696*** | 3.915*** |
| Natural attraction (%) | 4.521*** | 4.931*** | 5.223*** | 4.351*** | 4.458*** | 4.420*** |
| Recreational attraction (%) | −10.016*** | −11.471*** | −10.117*** | −2.173*** | −1.739*** | −2.513*** |
| Amusement/entertainment attraction (%) | 5.214*** | 6.949*** | 6.786*** | 3.621*** | 4.111*** | 4.851*** |
| Public transportation (%) | 2.919*** | 2.170*** | 1.912*** | 2.379*** | 2.162*** | 1.844*** |
| Accommodation (%) | 2.844*** | 3.473*** | 3.752*** | 1.676*** | 1.578*** | 0.395*** |
| Retail (%) | 3.467*** | 3.842*** | 3.508*** | 1.380*** | 1.533*** | 1.834*** |
| Nightlife (%) | −1.395*** | −1.094*** | −0.804*** | −0.305** | −0.174 | −0.692*** |
| Public service (%) | −2.192*** | −2.665*** | −4.277*** | −0.515** | −0.033 | −0.713*** |
| Education and health (%) | −6.309*** | −5.204*** | −2.516*** | −3.453*** | −2.836*** | −2.121*** |
| Other POIs (%) | −3.317*** | −3.304*** | −2.841*** | −1.419*** | −1.218*** | 0.693*** |
| *Revisitation* | | | | | | |
| Num. of prior visits | 0.383*** | 0.231*** | 0.133*** | 0.411*** | 0.233*** | 0.110*** |
| **Goodness of Fit** | | | | | | |
| Observations | 122,672 | 113,256 | 50,409 | 26,674 | 18,563 | 16,085 |
| Log-likelihood | −533,779 | −483,624 | −214,615 | −121,141 | −85,252 | −74,018 |
| Log-likelihood of null model | −788,747 | −726,548 | −321,701 | −171,290 | −117,499 | −101,436 |
| *pseudo-$r^2$* | 0.323 | 0.334 | 0.333 | 0.293 | 0.274 | 0.27 |
| *p* [chi-square] | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |

Note: ***: $p < 0.01$; **: $p < 0.05$; *: $p < 0.1$.

choices. Most variables have consistent directions of influence (positive or negative) across traveler groups. Specifically, the distance to the AOI has a negative influence on the likelihood of travelers selecting the AOI. Variables related to the functional characteristics of AOIs show diverse effects. To elaborate, the number of POIs within an AOI exerts positive effects, indicating that AOIs with larger quantities of POIs are more attractive. Its coefficients are larger among Asian travelers and those with longer stay, indicating that the number of POIs is particularly valuable to these travelers. POIs related to the attractions within an AOI show positive effects, except for the recreational attractions. Particularly, amusement/entertainment attractions present a greater influence among Asian travelers and those with longer stays.

POIs related to public transportation, accommodation, and retail facilities exert positive effects and present a higher utility for Asians. In contrast, nightlife, public service, education, and health POIs emerge as impediments that suppress the likelihood of travelers selecting the AOI. However, their negative effects are generally lower among Western travelers, indicating less antipathy of Western travelers. In addition, the number of prior visits to an AOI shows positive effects, indicating that travelers tend to return to the AOIs they have already been to during the

**Table 5**
MNL model results for travelers in Jeju.

| Nationality | Asian | | | Western | | |
|---|---|---|---|---|---|---|
| Length of stay (day) | 2–3 | 4–5 | ≥ 6 | 2–3 | 4–5 | ≥ 6 |
| | coef. | coef. | coef. | coef. | coef. | coef. |
| *Distance* | | | | | | |
| Distance to the AOI | −0.091*** | −0.099*** | −0.111*** | −0.092*** | −0.098*** | −0.114*** |
| *Functional characteristic* | | | | | | |
| Num. of POIs (log10) | 1.015*** | 1.000*** | 0.866*** | 0.949*** | 0.944*** | 0.763*** |
| Heritage attraction (%) | 3.798*** | 3.827*** | 2.967*** | 3.453*** | 3.287*** | 3.209*** |
| Natural attraction (%) | 1.125*** | 1.553*** | 1.258*** | 1.591*** | 1.627*** | 0.755*** |
| Recreational attraction (%) | 1.393*** | 1.907*** | 2.004*** | 1.500*** | 1.178*** | 1.517*** |
| Amusement/entertainment attraction (%) | 10.283*** | 9.627*** | 9.817*** | 8.101*** | 8.161*** | 7.205*** |
| Public transportation (%) | 7.600*** | 6.841*** | 6.607*** | 8.225*** | 7.367*** | 5.855*** |
| Accommodation (%) | −0.308*** | 0.068 | −0.140 | −0.019 | −0.069 | −0.999*** |
| Retail (%) | 0.914*** | 0.991*** | 1.010*** | 1.113*** | 0.751*** | 0.534 |
| Nightlife (%) | −13.13*** | −11.409*** | −7.699*** | −10.338*** | −9.726*** | −5.159*** |
| Public service (%) | −5.748*** | −6.279*** | −4.775*** | −5.642*** | −5.997*** | −1.372*** |
| Education and health (%) | −15.718*** | −16.286*** | −11.728*** | −12.278*** | −15.907*** | −4.131* |
| Other POIs (%) | 0.246*** | −0.129 | 0.124*** | 0.267*** | 0.148*** | 0.120*** |
| *Revisitation* | | | | | | |
| Num. of prior visits | 0.246*** | 0.231*** | 0.133*** | 0.411*** | 0.233*** | 0.110*** |
| **Goodness of Fit** | | | | | | |
| Observations | 32,122 | 43,259 | 12,881 | 5277 | 4397 | 1721 |
| Log-likelihood | −135,365 | −179,245 | −53,979 | −22,827 | −18,837 | −7,567 |
| Log-likelihood of null model | −189,340 | −254,747 | −74,017 | −29,956 | −24,348 | −9,194 |
| *pseudo-$r^2$* | 0.285 | 0.296 | 0.271 | 0.238 | 0.226 | 0.177 |
| *p* [chi-square] | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |

Note: ***: $p < 0.01$; **: $p < 0.05$; *: $p < 0.1$.

journey. However, its positive effects decrease as the length of stay increases, implying that more prior visits offer a diminishing value to travelers with longer stays.

### 4.2. Model results for Jeju

Table 5 presents the model results for travelers in Jeju. The models are well fitted with a pseudo-$r^2$ of 0.17–0.30. The variables also hold the same directions of influence in Jeju and Seoul, except for recreational attractions, accommodation, and other POIs in an AOI. Specifically, the distance to the AOI emerges as a negative factor in Jeju. Conversely, the number of POIs shows a positive influence. However, its influence decreases with longer stay, suggesting that the extra value of additional POIs diminishes as length of stay increases. All four types of attractions show a positive influence in Jeju, but this contrasts with our observations in Seoul.

Moreover, public transportation, and retail POIs in an AOI emerge as positive factors, whereas POIs related to nightlife, public service, education, and health have negative effects and exhibit a larger disutility among Asians. Conversely, accommodation POIs are not statistically significant or have a minor influence. This indicates that accommodation in an AOI is an insignificant or less profound factor in Jeju. Furthermore, the number of prior visits has positive effects but presents a diminishing influence with longer stay in Jeju.

### 4.3. Model results for Busan

The models for travelers in Busan (Table 6) are well fitted with pseudo-$r^2$ values ranging from 0.19 to 0.29. Most variables show similar influences in the three cities. The distance negatively affects the likelihood of travelers selecting the AOI in Busan, whereas the number of POIs emerges as a positive factor. Nevertheless, the influence of the number of POIs decreases with longer stay, aligning with the observations in Jeju. Besides, in line with Seoul and Jeju, POIs related to public transportation, heritage attractions, and natural attractions in an AOI exert positive effects. Moreover, POIs related to nightlife, education, and health facilities in an AOI are negative factors across the three cities, with a smaller influence among the Westerns and those with longer stays. Furthermore, the number of prior visits to the AOI has positive effects especially among travelers with longer stays.

A few factors exhibit unique effects in Busan. To elaborate, recreational attraction POIs are negative or insignificant factors, partially in line with our observations in Seoul but disagreeing with the results in Jeju. Amusement/entertainment attraction POIs generally exert a positive effect, aligning with the results in the other two cities. However, it shows a negative effect among Asian travelers who stayed in Busan for 2–3 days. Besides, while accommodation POIs tend to be negative or insignificant factors in Seoul and Jeju, this variable becomes a positive factor in Busan. Conversely, though retail POIs show positive effects in Seoul and Jeju, this variable emerges as a negative factor among Asian travelers with 2–5 days of stay, but it becomes an insignificant factor among Western travelers with a 2 or 3-day stay in Busan. Furthermore, public service POIs tend to have positive effects in Busan, reversing its direction of influence in Seoul and Jeju.

### 4.4. Relative importance of the variables: comparison across cities and traveler groups

To evaluate the relative importance of factors, we measure the elasticity of each variable (Fig. 6). The magnitude (absolute value) of elasticity indicates the extent to which the choice probability varies with a change in the variable, i.e., level of importance, and its sign (positive or negative) aligns the coefficient in MNL models, i.e., direction of influence.

Notably, three variables tend to have the greatest elasticity magnitudes in all cases, being the most important factors. These variables include the number of POIs in an AOI, the distance and the number of prior visits to the AOI. To elaborate, the number of POIs holds the largest elasticity. A one-percent increase in this variable can result in a 3.5 %–6.8 % probability rise. Among variables with negative effects, the distance has the greatest or second-greatest elasticity magnitude, corresponding to a 0.27 %–0.56 % probability decrease. The number of prior visits typically has the second or third largest elasticity, corresponding to a 0.057 %–0.51 % probability increase.

In contrast, POIs related to the attractions generally have the lowest importance. Similarly, public service and other POIs also tend to hold

**Table 6**
MNL model results for travelers in Busan.

| Nationality | Asian | | | Western | | |
|---|---|---|---|---|---|---|
| Length of stay (day) | 2–3 | 4–5 | ≥ 6 | 2–3 | 4–5 | ≥ 6 |
| | coef. | coef. | coef. | coef. | coef. | coef. |
| *Distance* | | | | | | |
| Distance to the AOI | −0.198*** | −0.222*** | −0.298*** | −0.218*** | −0.240*** | −0.269*** |
| *Functional characteristic* | | | | | | |
| Num. of POIs (log10) | 1.132*** | 1.126*** | 0.891*** | 0.800*** | 0.839*** | 0.778*** |
| Heritage attraction (%) | 12.809*** | 13.720*** | 13.209*** | 11.945*** | 12.846*** | 9.887*** |
| Natural attraction (%) | 12.384*** | 12.918*** | 10.447*** | 9.983*** | 9.931*** | 7.784*** |
| Recreational attraction (%) | −5.746*** | 0.766 | −5.831** | −6.259*** | −7.024*** | −0.446 |
| Amusement/entertainment attraction (%) | −47.167*** | −0.692 | 88.731*** | 45.011** | 116.569*** | 118.957*** |
| Public transportation (%) | 23.805*** | 21.898*** | 14.975*** | 17.926*** | 16.859*** | 7.495*** |
| Accommodation (%) | 3.223*** | 2.643*** | 1.992*** | 5.776*** | 6.317*** | 4.239*** |
| Retail (%) | −2.007*** | −0.121 | 4.407*** | −0.405 | 0.738* | 2.506*** |
| Nightlife (%) | −17.354*** | −16.34*** | −9.363*** | −12.555*** | −15.348*** | −9.424*** |
| Public service (%) | 6.918*** | 4.043*** | −1.163 | 3.682*** | 2.083*** | −3.403*** |
| Education and health (%) | −9.632*** | −7.837*** | −6.222*** | −3.902*** | −2.613*** | −3.388*** |
| Other POIs (%) | −1.708*** | −1.808*** | −1.060*** | −0.625** | −0.556 | −1.271** |
| *Revisitation* | | | | | | |
| Num. of prior visits | 0.068*** | 0.046*** | 0.103*** | 0.248*** | 0.136*** | 0.071*** |
| **Goodness of Fit** | | | | | | |
| Observations | 19,248 | 9,185 | 2,676 | 4,940 | 2,599 | 1,958 |
| Log-likelihood | −79,911 | −37,825 | −10,500 | −21,769 | −11,350 | −8,405 |
| Log-likelihood of null model | −112,698 | −52,235 | −14,283 | −27,889 | −14,088 | −10,561 |
| *pseudo-$r^2$* | 0.291 | 0.276 | 0.265 | 0.219 | 0.194 | 0.204 |
| *p* [chi-square] | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |

Note: ***: $p < 0.01$; **: $p < 0.05$; *: $p < 0.1$.

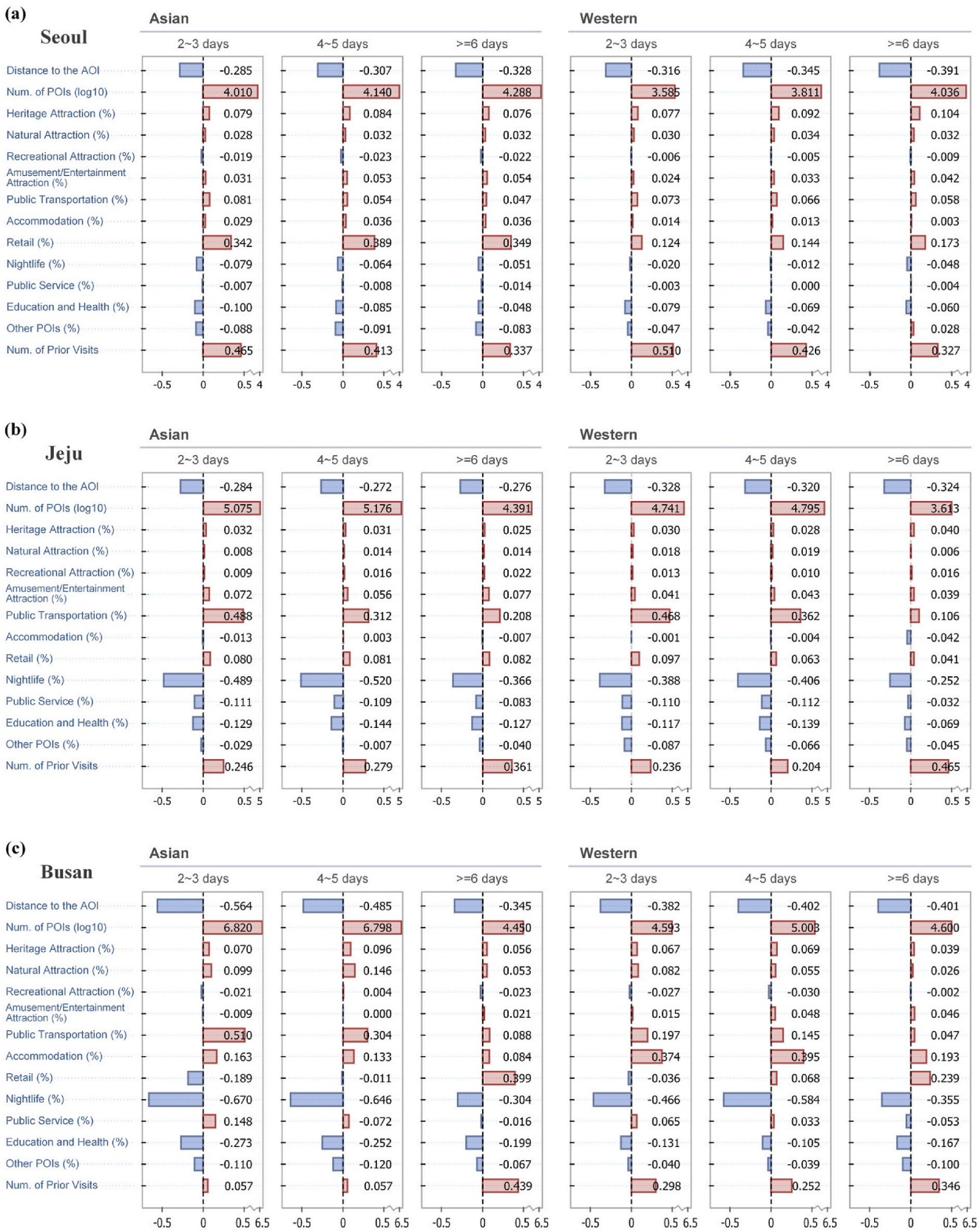


**Fig. 6.** Aggregate direct elasticity of the variables for travelers in (a) Seoul, (b) Jeju, and (c) Busan.

minor importance. The results indicate that, while these factors do have an influence, further changes in their relative amount in AOIs would not lead to a substantial shift in the choices. It suggests that spatial choices may be more sensitive to the presence of these attractions and facilities in an AOI.

Several variables are found to be uniquely important in specific cities but do not hold comparable importance in all cities. To elaborate, retail POIs in an AOI rank the second or third most important factor in Seoul. Public transportation POIs typically hold the second or third greatest importance in Jeju and Busan. Accommodation POIs have a high elasticity in Busan, especially among the Westerns. Moreover, among variables with negative effects, nightlife POI holds the largest or second-largest elasticity in Jeju and Busan.

The importance of most factors is generally comparable across nationalities and lengths of stay. Nevertheless, some factors have varied importance across traveler groups. To elaborate, the distance tends to be less important among Asians, suggesting that their spatial choices are less sensitive to extra movement distance. In contrast, the number of POIs is a more important factor among Asians. Moreover, nightlife, education and health, and other POIs, which exert a negative influence, are less important among the Westerns and those with longer stays, especially in Jeju and Busan. In addition, the importance of public transportation POIs appears to decrease with longer stays.

Furthermore, certain variables are uniquely important in specific cases. Public transportation POIs in Busan, and retail POIs in Seoul, are of greater importance among Asian travelers. In Busan, the number of prior visits emerges as a less important factor among Asian travelers with 2–5 days of stay. In contrast, accommodation POIs are a notably important factor among Western travelers in Busan.

## 5. Discussion and implication

This study introduces a holistic framework that combines tourism big data and discrete choice models to investigate how tourists' spatial choices within cities are affected by different factors. An AOI identification process is adopted on the check-in data to convert POIs into a manageable choice set that captures the majority of trips. An elasticity analysis is employed to quantify the relative importance of each factor. The case study, focusing on international travelers in three South Korean cities, demonstrates that the spatial choices of tourists for intra-urban travel can be effectively modeled using our framework in spite of differences in urban morphology or travel patterns. Our findings offer valuable insights into tourist consumer behavior by identifying the most important factors in determining the spatial choices in cities and unveiling the factors with universal and unique effects across cities and tourist groups.

### *5.1. Key factors in determining the spatial choices*

The elasticity results highlight three key factors in determining the spatial choices: the number of POIs in an AOI, the distance to the AOI, and the number of prior visits to the AOI during the same city journey. The three factors hold the greatest relative importance. Travelers' spatial choices are highly sensitive to the changes in these factors. The analysis across different cities and travel groups shows that the effects and importance of these factors tend to be universal across urban destinations and traveler groups.

The three key factors suggest the primary inclination of travelers when making spatial decisions for intra-urban travel: they seek areas with a higher concentration of attractions and facilities, aim to reduce movement distance, and often revisit places during the same city journey. This implies that travelers generally follow the logic of rational choice in making spatial decisions, aiming to maximize their activity opportunities while minimizing effort and unfamiliarity. These findings emphasize the significant force of business concentration in boosting the tourist demand in a place (Yang, 2012) and reaffirm that intra-urban travel demand decays with increasing movement distance (Jin et al., 2018).

Our findings also suggest that repeat visitation behavior is not limited to the context of inter-destination travel.It is also significant within intra-urban travel. However, our observation contradicts the findings of Li et al. (2019), who noted that tourists in a destination are unlikely to return to locations they have visited. The disparity may be attributed to the spatial scale under consideration. Tourists may revisit a popular area in a city but not necessarily a specific site (e.g., a museum) within the area. While little attention has been given to repeat visits during intra-urban travel, this suggests an important yet understudied aspect of tourist intra-urban behavior.

### *5.2. Universal vs. city-specific influences on traveler's spatial choices*

Several factors, besides those discussed in Section 5.1, exhibit a universal influence across the three cities. As evidenced through the MNL model results, heritage attractions, natural attractions, and public transportation facilities within an AOI positively influence the likelihood of travelers selecting the AOI. Conversely, POIs related to nightlife, education, and health show negative effects. These findings imply that travelers tend to value these elements and city offerings similarly across the cities, indicating a degree of predictability in spatial choices.

However, we find that spatial choices are affected in different ways across cities. Five factors either positively or negatively influence the choices, and their effects vary from one city to another. These factors include recreational attractions, amusement/entertainment attractions, accommodation, retail, and public service POIs within an AOI. Their city-specific effects may be attributed to the unique features of urban destinations and the distinct travel purposes of urban visitors. This underscores the particularities of the cities and highlights an aspect of variability in tourists' spatial preferences.

Factors such as heritage attractions, natural attractions, public service, education, and health facilities in an AOI are of minor importance, meaning that further changes in these factors may not result in a substantial shift in travelers' spatial choices. This pattern appears consistently across the three cities. The findings have two implications. First, travelers may prioritize the presence or quality of these attractions and facilities in an AOI rather than their relative amount. Second, these factors may have reached a saturation point within the AOIs, presenting a marginal effect on boosting tourist demand. These insights further suggest that improving the attractiveness of a place requires a synergistic approach, integrating various elements and preventing excessive development of single attractions or facilities.

Conversely, certain factors hold unique importance in specific cities. Changes in these factors may lead to a significant shift in the choice probability, but this cannot apply universally across cities. For instance, public transportation and nightlife facilities in an AOI are particularly important in Jeju and Busan. In contrast, retail facilities hold greater importance in Seoul, while accommodation facilities are more important in Busan. These findings suggest that standardized development strategies may not effectively stimulate the shift in tourist intra-urban demand across different urban destination contexts.

### *5.3. Impact of traveler's nationalities and lengths of stay*

Our results indicate that the influence of factors is largely consistent for both Asian and Western travelers, irrespective of their length of stay. In each of the three cities, these factors tend to be comparably important and affect spatial choices similarly across different groups. This suggests that the overall spatial preferences of those travelers might be, to some extent, generalized rather than completely disparate. This implies that, despite from different countries or with different lengths of stay, travelers may generally seek similar tourism experiences within the cities.

Meanwhile, certain factors exhibit different levels of importance between Asian and Western travelers. Specifically, the number of POIs is

more important for Asian travelers, whereas distance holds less importance. This suggests that Asian travelers prioritize places with a higher concentration of attractions and facilities, and they are more willing to accept extra distance to reach those places. In contrast, Western travelers are less deterred by AOIs with more nightlife, education and health, and other POIs. This indicates a broader openness of Western travelers to nightlife and residential parts of the cities, possibly due to a greater sense of novelty and greater cultural distance from South Korea.

Longer length of stay in the cities is associated with a reduced influence and importance of factors such as public transportation facilities within an AOI. It indicates that the spatial choices of travelers with longer stays are less susceptible to public transportation availability. Besides, the negative influence of nightlife, education, and health facilities in an AOI also diminishes with longer stays, suggesting a decreased reluctance to explore the nightlife places and more residential parts of the cities. This implies that extended stays could facilitate more comprehensive exploration of the cities, agreeing with the prior finding that longer stays can broaden the scope of activities and enrich the travel experience at a destination (Pearce, 1988).

### 5.4. Theoretical implications

Our study underscores the potential of leveraging tourism big data and discrete choice modeling to analyze both city-wide and small-scale spatial decisions of tourists. Given the limited availability of travel-related choice data of tourists at destinations (Bursa et al., 2022a, 2022b), our framework utilizes mobile positioning data to derive the spatial choices of tourists within cities. The case study further demonstrates that spatial choices within cities can be effectively explained by discrete choice models, i.e., through a microeconomic formulation of utility maximization. This supports the notion that tourists' spatial decisions largely align with rational choice principles (Morley, 1994), particularly in the context of intra-urban travel. Furthermore, our framework can be expanded to incorporate more sophisticated influences on spatial choices. For instance, the MNL models can be replaced with generalized spatially correlated logit models (Sener et al., 2011) to account for the spatial correlation effects between AOIs.

This study reaffirms that factors influencing tourists' spatial choices in cities are complex (Caldeira & Kastenholz, 2020). We further introduce a critical dimension, i.e., relative importance, to assess the influence of factors. The findings suggest that the spatial choices are not equally sensitive to variation in the influencing factors, emphasizing the need to consider how tourists prioritize different factors when making spatial decisions. Therefore, treating all factors in an undifferentiated way may lead to inaccurate predictions of intra-urban travel demand regarding future changes in urban destination environment. We also find that travelers' spatial choices are not affected in the same way across the cities. Certain factors are found to have a universal influence across the cities, while other factors tend to have unique effects in specific cities. This supports the proposition that urban tourism planning should avoid one-size-fits-all approaches (Chang & Huang, 2008). Furthermore, we also reveal that, even if certain factors are universally appealing (e.g., public transportation POIs) or repulsive (e.g., nightlife POIs), their levels of importance may vary across the cities. Additional changes in these factors may not induce a substantial shift in tourists' spatial choices in every urban context. This implies that single urban tourism concepts may not be applicable to all cities, as tourists may not respond to the same urban tourism practices as significantly as they do elsewhere. Urban tourism strategies should be customized based on the unique characteristics of each city. This could lead to a more tailored approach in urban tourism planning and marketing.

For example, when examining tourists' spatial behavior through the lens of time geography (Hägerstrand, 1970, pp. 143–158), the presence of vibrant nightlife attractions is likely to extend tourists' time budgets into the evening hours. This effect is more pronounced in cities with higher levels of security compared to those perceived as more dangerous. This nuanced understanding advances existing theories by highlighting how specific urban contexts can alter traditional assumptions about tourists' spatial behavior, emphasizing the need for tailored strategies that account for these unique urban settings.

In addition, our framework highlights the significance of repeat visits in shaping tourists' spatial choices. Given that revisit intention is a crucial factor for the survival and growth of the tourism industry, understanding the key elements that influence visitors' intentions to revisit is essential. Revisit intention encompasses future behaviors of travelers, including decision-making, destination selection, and post-trip assessment, and serves as a primary driver for the expansion of tourism marketing operations (Chang et al., 2019; Soliman, 2021). By integrating insights about revisit intentions and context-specific variability in the importance of various factors, our findings contribute to advancing the Theory of Planned Behavior in the tourism context (Ajzen, 1991). This enriched understanding of tourists' travel preferences and intentions provides valuable guidance to tourism management. It helps in crafting effective marketing strategies that align with the psychological drivers of positive travel decisions, ultimately encouraging new visits or repeat visits.

The findings of this study also suggest that the spatial preferences of travelers from Asian and Western countries, as well as those with different lengths of stay, may be characterized by variations within a generalized pattern, rather than entirely unique patterns. Understanding the preferences of travelers from different cultural backgrounds brings benefits in fostering a city's cultural branding and promoting cultural exchange. Exposing culturally significant sites to targeted tourist groups with larger culture gaps can enhance cross-cultural dialogue, and potentially increase the attractiveness of these sites to diverse audiences.

Climate change significantly impacts travel behavior, as extreme weather conditions influence tourists' decisions and preferences. This research demonstrates the potential of leveraging tourism big data and discrete choice modeling to analyze tourists' spatial decisions, incorporating the relative importance of various factors. By integrating weather or climate big data into this framework, we can gain insights into how tourists consider weather factors, such as rain, wind, humidity, and heat waves, in their spatial choices. Understanding these considerations would enable a city to strategically distribute and promote indoor facilities in attractions to ensure a good travel experience for tourists regardless of weather conditions, thereby enhancing the resilience of its tourism economy to climate change and the extreme weather conditions it may bring (Gössling et al., 2012; Kubo et al., 2020).

### 5.5. Practical implications

Our findings highlight the adaptability in urban tourism planning and management. By understanding how tourists prioritize different destination features, local planners can develop targeted strategies to enhance visitor experiences and economic resilience. For example, as public transportation facilities in the AOIs are of greater importance in Jeju and Busan, decision-makers in these cities can prioritize investments such as expanding shuttle services to peripheral attractions or introducing real-time transit apps tailored for tourists. Conversely, Seoul can focus on developing vibrant shopping districts with local artisan products or promoting pop-up markets during peak seasons to capitalize on tourists' strong preference for retail experiences. These tailored investments ensure resources are allocated efficiently, avoiding developments that do not align with visitor priorities.

Cities can further enhance tourism by targeting specific visitor segments with customized offerings. For instance, Western travelers in Jeju and Busan, who are less deterred by nightlife, education, and health-related amenities, can be targeted with immersive cultural experiences, such as guided night market tours. Similarly, travelers with longer stays, who are more open to exploring residential areas and nightlife, could be encouraged through extended-stay packages that promote local festivals or community-based activities. In Busan, marketing campaigns

highlighting high-quality accommodations can attract Western tourists, while Asian travelers in Seoul and Busan can be drawn to curated retail and transit-focused experiences. Extending the length of stay of tourists through such targeted strategies may help distribute tourism benefits more broadly across local businesses and communities.

Tailored strategies should also be considered at different stages of the Tourism Area Life Cycle (TALC) (Butler, 1980) based on the variability in the influence of factors on tourists' spatial behavior. For attractions at the Development Stage, infrastructure and amenities become more important. Factors affecting tourists' spatial choice might shift towards convenience, such as transportation options, accommodation quality, and dining experiences. Tourists might start to value comfort and accessibility more, reflecting a change in preferences as the destination becomes more mainstream. In the Consolidation Stage, the destination is well-established, and the market becomes more segmented. Different tourist segments prioritize different aspects, such as photo taking, stamp rally, or shopping for souvenirs. Tailored marketing strategies become crucial to cater to diverse preferences. Meanwhile, certain attention should be paid to the over-tourism problem that may accelerate the transition to the Stagnation and Decline Stage.

Furthermore, our framework enhances data-driven tourism planning by enabling more precise demand predictions. Destination managers can use predictive models to prioritize investments, such as expanding key attractions in Seoul or transit networks in Jeju and Busan, based on tourist tracking and inferred tourist preferences. By modeling demand shifts from competing areas, planners can optimize resources and target travelers with data-driven marketing campaigns (Cronjé & du Plessis, 2020; Crouch et al., 2019).

### 5.6. Limitations and future research directions

This study has a few limitations. The discrete choice models do explain the outcome of spatial decisions but do not address the underlying motivations of tourists. The variables selected do not cover the factors in relation to attitude and perception. To investigate the decision process and incorporate psychological factors, hybrid choice models could be a promising substitute to traditional discrete choice models (Kemperman, 2021). Furthermore, we do not consider any interdependency between the choices. However, a tourist's travel decisions are often interrelated over time. Exploration of such interdependency might be an area for future research.

To further enhance the understanding of travelers' spatial choices, future research can enhance the modeling by incorporating more accurate and context-specific techniques. One promising direction is the use of mixed logit models, which account for random effects and can capture the distribution of preferences within groups, thereby providing insights into the heterogeneity of traveler behavior. This approach allows for a more nuanced understanding of how different factors influence choices across diverse segments of the population. Besides, integrating the three destinations into a single model with interaction terms could strengthen the analysis by enabling cross-city comparisons. Such a pooled model would highlight both differences and commonalities in traveler behavior across urban contexts. By utilizing larger datasets, this approach could achieve narrower confidence intervals, leading to more precise estimates and richer insights. Moreover, spatially correlated models can be particularly beneficial in contexts where spatial dependencies are strong and cannot be adequately captured by regular MNL models. This approach would allow us to better account for spatial heterogeneity and improve the accuracy of the models in such contexts. These methodological improvements would offer a more comprehensive understanding of the factors driving travelers' spatial choices and inform urban planning and tourism management strategies.

Additionally, certain limitations may influence the interpretation of our findings. One key limitation is the assumption that tourists make rational choices, which may not fully capture the influence of supply-side factors such as how the attractions are promoted by different tourism marketing strategies. These factors can guide tourist behavior and potentially shape observed patterns of choice. Furthermore, decisions are often made under time constraints, with limited information, and in unfamiliar settings, suggesting the relevance of bounded rationality and heuristic-based behavior. Future research could benefit from incorporating insights from behavioral economics and psychology to better understand the impact of the non-rational elements influencing tourist decisions. Another limitation of this study is the use of pre-COVID-19 data, which may not fully capture the shifts in spatial choice decision process and travel behavior that have emerged post-pandemic. The pandemic has potentially altered tourists' spatial choices, with increased emphasis on safety, hygiene, and social distancing (Zheng et al., 2021). These changes might influence preferences for private transportation, less crowded attractions, outdoor spaces, contactless services, and destinations perceived as more hygienic (Park, Kim, et al., 2021; Song et al., 2025). Therefore, future research should consider post-COVID data to explore how these shifts have impacted tourist decision-making and spatial behavior.

## CRediT authorship contribution statement

**Ke Mai:** Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Formal analysis, Data curation, Conceptualization. **Yang Xu:** Writing – review & editing, Supervision, Resources, Project administration, Funding acquisition, Data curation, Conceptualization. **Xinyue Chen:** Writing – review & editing, Validation. **Hengyun Li:** Writing – review & editing. **Sangwon Park:** Writing – review & editing, Resources.

## Impact statement

Quantifying tourists' spatial choices within cities and the factors shaping these onsite decisions remain challenging due to data and methodological constraints. This study introduces a holistic framework integrating mobile positioning data and discrete choice models to bridge this gap. Our study of international travelers in three South Korean cities reveals that travelers' spatial choices are predominantly determined by the desire to visit places with more attractions and facilities, minimize travel distance, and revisit certain places during the same journey. The results also suggest that enhancing place attractiveness requires synergizing various types of attractions and facilities, rather than over-developing single-type elements. The study further identifies factors with city-specific effects, suggesting that there is no one-size-fits-all strategy. Finally, the study highlights how certain factors influence travelers differently depending on their nationalities and lengths of stay, suggesting that cities should tailor their destination planning and marketing strategies to better accommodate travelers' spatial preferences.

## Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author(s) used ChatGPT in order to improve readability and identify grammatical errors. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

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## Appendix

**Table A.1**
Comparison of mixed MNL model and Regular MNL model on a small sample

| Coefficient | Mixed MNL model | | Regular MNL model | |
|---|---|---|---|---|
| | Estimate | Std.Err | Estimate | Std.Err. |
| Distance to the AOI | −3.819*** | 0.026 | −3.801*** | 0.024 |
| Num. of prior visits | 0.140*** | 0.005 | 0.121*** | 0.004 |
| Num. of POIs (log10) | 1.966*** | 0.015 | 1.873*** | 0.012 |
| Commercial attractions | 2.853*** | 0.133 | 3.327*** | 0.110 |
| Transportation | 3.184*** | 0.138 | 3.235*** | 0.124 |
| Government and Agency | 1.103*** | 0.231 | 1.198*** | 0.202 |
| Recreation Facility | −1.344*** | 0.186 | −1.279*** | 0.175 |
| Amusement/Entertainment | −0.029 | 0.197 | 0.463* | 0.183 |
| Education | −4.902*** | 0.299 | −2.845*** | 0.181 |
| Health | −11.356*** | 0.483 | −7.970*** | 0.371 |
| Accommodation | 3.504*** | 0.203 | 3.741*** | 0.183 |
| Recreational attraction | −2.167*** | 0.454 | −2.296*** | 0.432 |
| Industrial attraction | 1.766*** | 0.495 | 2.103*** | 0.423 |
| Heritage/Culture attraction | 3.291*** | 0.084 | 3.519*** | 0.076 |
| Others | −0.882*** | 0.153 | −0.677*** | 0.123 |
| Personal services | −4.862*** | 0.636 | −3.269*** | 0.424 |
| sd. Distance to the AOI | 1.198*** | 0.058 | | |
| sd. Num. of prior visits | 0.099*** | 0.010 | | |
| sd. Num. of POIs (log10) | −0.440*** | 0.038 | | |
| sd. Commercial attraction | −2.262*** | 0.321 | | |
| sd. Transportation | 0.115 | 1.641 | | |
| sd. Government and Agency | 0.049 | 2.959 | | |
| sd. Recreation Facility | 0.068 | 1.954 | | |
| sd. Amusement/Entertertainment | 0.084 | 1.943 | | |
| sd. Education | 3.048*** | 0.228 | | |
| sd. Health | 7.570*** | 0.406 | | |
| sd. Accommodation | 0.017 | 1.716 | | |
| sd. Recreational attraction | 0.002 | 3.530 | | |
| sd. Industrial attraction | −0.342 | 3.825 | | |
| sd. Heritage/Culture | −0.008 | 0.564 | | |
| sd. Others | −0.723 | 0.564 | | |
| sd. Personal service | 5.400*** | 0.964 | | |
| Goodness of Fit | | | | |
| Observations | 19,785 | | 19,785 | |
| Estimation time (seconds) | 3,073.8 | | 193.3 | |
| Log-Likelihood | −85,957.914 | | −86,259.645 | |
| Log-Likelihood of the null model | −128,657.701 | | −128,657.701 | |
| AIC | 171,979.828 | | 172,551.290 | |
| BIC | 172,232.394 | | 172,677.573 | |
| pseudo-r2 | 0.332 | | 0.330 | |

Note: ***: $p < 0.001$; **: $p < 0.001$; *: $p < 0.05$.

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