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Analyzing the Influence of Visitor Types on Location Choices and Revisit Intentions in Urban Heritage Destinations

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Abstract: Understanding visitors' spatial choice behavior is important in developing effective policies to counteract overcrowdedness in attractive urban heritage areas. This research presents a comprehensive analysis of visitor location choice behavior, aiming to address two primary objectives. First, this paper investigates the relationship between visitor segments and the choice of particular Points of Interest (POIs). Second, this paper explores the impacts of visitors' experiences and visitor segments on their revisit intentions. We used a sample of 320 visitors who had been to Amsterdam within the last five years to collect data about their location choice behavior and intention to revisit after a recent visit to the city. Combining the revealed choices and intentions of pre-defined visitor segments obtained from a stated choice experiment, association rules are extracted to reveal differences in the patterns of behaviors related to the segment. The findings identify associations between various POIs, including museums such as the Rijksmuseum and Madame Tussauds, and visitor classes, which include "cultural attraction seekers", "selective sightseers", and "city-life lovers". Furthermore, binary logistic regression analysis reveals that affective experiences, such as feelings of comfort, happiness, and annoyance, have a significant influence on visitors' intentions to revisit the destination in the future. This research found that "cultural attraction seekers" and "selective sightseers" display a higher likelihood of considering a return visit to the city.

Keywords: Apriori algorithm; association rule mining; density map; location choice behavior; revisit intention; urban heritage tourism; visitor segmentation

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1. Introduction

The rapid expansion of urban tourism has burdened historic centers [1,2], leading to overcrowding at heritage sites [3]. While some heritage sites attract attention from visitors [1], others struggle despite their historical value. Understanding visitors' location choice behavior is important when identifying the reasons that make specific tourist locations attractive and the factors that create loyalty, which influence visitors' decisions relating to future visits [4]. The existing literature recognizes elements, such as visit experience [5], destination image [6,7], and motivation [8,9], to explain visitors' location choice behavior, which is critical for addressing overcrowdedness challenges in historical cities.

In tourism studies, the importance of taking the characteristics of visitors into account is emphasized for the analysis of visitors' location choice behavior [10,11] and motivations [12,13]. Identifying distinct visitor segments contributes to understanding where visitor groups cluster, their preferences within these clusters, and their motivations [14]. Many studies [15–19] have stated the importance of visitor segmentation based on choice behavior, recognizing that visitors have different needs that require distinct attention in tourism management and marketing [20]. Distinguishing the most suitable segments for a touristic location enables customized marketing and tailored tourism products to meet specific group needs. Furthermore, the composition of visitor segments helps to identify the determinants of visitor satisfaction levels and visitor intention to revisit a place [21–23].

Examining individuals' location choice behavior in real-world settings is critical for identifying actual tourist behavior, focusing on what tourists do rather than what they say they will do in a survey [24,25]. With the emergence of digital technologies, large volumes of data from GPS-enabled devices [26–28], data from volunteered geographic information (VGI) platforms, such as location-based social networks (i.e., Flickr and Instagram), and sharing platforms (i.e., Airbnb and Trip Advisor) [29–34] have become available and have been employed in studies to explain visitors' actual location choice behaviors in time and space. These studies demonstrate the potential of location-based data in revealing visitors' choice of Points of Interest (POIs), movement patterns between POIs, and their expressions of affective experiences about POIs. However, these data sources have shortcomings, such as their unrepresentative samples and lack of information about personal characteristics and visitor motivations. Therefore, there is still limited information about the characterization of visitors from these datasets, especially regarding the composition of visitor segments. To address these limitations, it is important to have a more tailored approach where the self-reported personal and location data of visitors are collected in addition to experiences, intentions, and the actual choices made.

While many studies have contributed valuable insights into visitors' overall spatial behavior in historical cities [35–38], there is still a knowledge gap concerning the relationship between visitor segments and preferences for specific Points of Interest (POIs). This relationship is essential for deriving policy measures to counteract overcrowding at particular locations, which is increasingly a concern in historical cities. Visitor intentions to revisit is an early indicator of their future behavior [39]. It is well-established that future returns to a destination are linked to positive experiences and the satisfaction of visitors with a destination visited [40–42]. Furthermore, the image of the destination significantly influences the decision making and travel behavior of visitors [6,42]. Although recent tourism studies acknowledge the influence of experiences on revisit intentions, there remains a gap in the classification of experiences as a factor in revisiting intentions and possible differences between visitor segments regarding this relationship.

The complex interaction between a visitor segment and individual preferences to visit specific activity locations (POIs) has received limited attention. Distinguishing between segments in visitors' location choices in terms of heritage sites provides better control over visitor movements and insight into opportunities to reduce crowding in popular neighborhoods. Therefore, this study aims to address this research gap by employing a multifaceted approach. It seeks to uncover the distinct preferences of visitor segments for specific POIs, subsequently influencing their intentions to revisit historical sites. By achieving a more detailed understanding of these dynamics, this research aims to contribute to urban heritage tourism management and research, with an emphasis on addressing problems related to overcrowdedness.

Accordingly, the purpose of this study is twofold: (i) to identify the relationship between the visitor segment and tendencies to choose particular POIs on a historical city trip and (ii) to analyze the impacts of visitors' experiences and visitor segment on revisit intentions. For this purpose, an online survey was used to collect data on visitors' location choices, experiences, and revisit intentions from a random sample of 320 individuals who had recently taken a city trip to Amsterdam. We used results obtained from latent class analysis to identify visitor segments. The Apriori algorithm was applied to mine the data and derive association rules relating segments to types of POIs visited. A binary logistic regression analysis was conducted to explain revisit intentions based on experiences, perceptions, and segments.

The remainder of this paper is structured as follows. Section 2 reviews related work focused on visitor segmentation and analysis of POI attractiveness based on location choice and revisit intention data. Section 3 focuses on the research design and research methods used in this study. This is followed by a discussion of the results in Section 4. Finally, a discussion of the conclusions in Section 5 completes the paper.

2. Related Work

This study integrates several elements introduced above: the necessity to describe visitor segments, which allows an understanding of their specific location choices, and the determination of visitors' activity locations (POIs) based on location data. Furthermore, this study aims to reveal visitors' revisit intention for these POIs. This section presents a literature review of these elements.

2.1. Visitor Segmentation

The identification of distinct visitor profiles is essential for describing visitors' preferences and location choice behavior, as each tourism destination exhibits unique attributes catering to specific needs that may differ between tourist segments [15–18,43]. These profiles can be distinguished based on individuals' preferences, personal characteristics, and motivations that influence their choice of destinations. Consequently, tourists who visit specific areas tend to exhibit similar profiles such as common preferences, motivations, expectations, and patterns of movement [14]. Insight into these profiles contributes to a better understanding of the spatial behavior patterns of visitors.

Espelt et al.'s study [15] focuses on identifying internally homogenous and externally different groups resulting in four visitor segments for the city of Girona: noncultural tourists, ritual tourists, interested tourists, and erudite tourists. Three groups of factors were identified to differentiate the composition of visitor segments, including sociodemographic conditions, characteristics of the visit, and psychological elements of the tourist. They find that travel company is a stronger identifier of visitor segments compared to sociodemographic conditions.

Oppermann [17] focuses on identifying the spatial behavior of international tourists in Malaysia. The study considers sociodemographic characteristics, purpose of visit, group size, and previous visit information to identify spatial behavior patterns at both aggregate and disaggregated levels. The tourists are divided into two segments: pleasure travelers and travelers with other purposes, and each segment exhibits different travel patterns, with the latter segment concentrating on specific areas, primarily major economic and population centers. Variables such as country of residence and number of overnight destinations distinguish the specific market segments. This highlights how dispersed tourist activities contribute economically to spatial inequalities. Additionally, Lau and McKercher's [16] study aims to reveal intra-destination movement patterns among visitors based on first-time and repeat visit segments. The findings show that repeat visitors exhibit more varied movement patterns on the first day of a return visit, while first-time visitors show a more restricted pattern, exploring the vicinity of their accommodation within their tourist bubble.

Silberberg [18] and Lord [43]'s research on visitors to Ontario segments cultural tourists in a concentric circle based on the degree to which culture defines the motivation for making the trip. The smallest circle comprises individuals "greatly motivated" by culture who specifically travel to the city for its cultural offerings such as museums, cultural festivals, and theater. Additionally, individuals with higher education and higher income are highly likely to travel and tend to be more interested in culture within this segment. The second group represents individuals "in part motivated" by culture, combining cultural interest with other reasons such as visiting friends and relatives or seeking relaxation by nature. The third group includes people for whom culture is an "adjunct" to another main motivation. Their primary reason for visiting might be hiking, but they plan to incorporate cultural activities. The outer circle includes "accidental cultural tourists", comprising individuals who would not engage with a cultural attraction or event under any circumstances; hence, it is not advisable to target them in marketing efforts.

The findings of these studies confirm the significance of identifying distinct visitor profiles to comprehend their preferences and choice behavior in tourism activities. The diversity of visitor segments, shaped by factors such as personal characteristics and motivations, contributes to the formation of common patterns of movement that differ between segments. Recognizing visitor segments and considering factors such as visit patterns, motivations, and preferences are, therefore, important to manage attractions and improve visitor experiences.

As discussed in previous literature, the identification of distinct visitor profiles provides a foundation for understanding visitors' preferences and location choice behavior. While prior studies, such as those by Espelt et al. [15], Oppermann [17], Lau and McKercher [16], Silberberg [18], and Lord [43], have contributed different perspectives to the segmentation of visitor populations based on various factors such as sociodemographic characteristics, purpose of visit, and travel patterns, these studies do not specifically focus on urban heritage tourism, especially in the context of overcrowded attractive heritage areas. To overcome these challenges, extensive visitor information becomes critical, collected through visitors' self-reported information, to examine detailed visitor segments.

2.2. POI Definition with Location-Based Data

With the advancement of Information and Communications Technology (ICT), the Internet of Things (IoT) and big data, such as urban geolocated data from social media, have become widely available, providing useful information to enhance the understanding of where people are, what they do, and what they value [44–46]. The domain of big data in tourism research primarily derives from three data sources, including users, devices, and operations [47]. Focusing on user-generated content, these data can be further categorized as online textual and online photo data.

Online textual data serve as an information source containing reviews, comments, and descriptions that provide rich and detailed information about tourists' experiences, perceptions, and opinions. These insights can be useful for distinguishing visitors' experiences and their levels of satisfaction. Online textual data are sourced from various platforms such as TripAdvisor [32,48,49], Booking [50], Expedia [51], and Airbnb [33]. As stated by Li et al. [47], TripAdvisor stands out as one of the largest and the most popular tourism social media sources. Such data sources are utilized for detecting hotspot and coldspot areas, evaluating secondary tourism products, and revealing tourists' heritage experiences.

For instance, Ganzaroli et al. [48] focused on how TripAdvisor influences the perceived quality of restaurants within Venice's urban heritage context, revealing that the ranking of the restaurants on TripAdvisor is closely linked to quality rather than popularity. The study conducted by van der Zee et al. [32] explored the distribution of tourists within urban heritage areas using TripAdvisor data. Their study involves a spatial analysis of TripAdvisor data to identify tourist activity locations (POIs) and proceeds to validate these findings with policymakers and to convert User-Generated Contents (UGC) into insights for decision-makers. The authors emphasized the importance of effective management of tourist visits to prevent overcrowding and potential deterioration of heritage locations. Moreover, they argue that the integration of these contents with additional sources could significantly enhance their effectiveness.

In that sense, online textual data from TripAdvisor, with its rich source of user-generated content, reviews, and information about POIs, are a valuable tool for identifying the relationship between POIs and particular visitor segments. However, leveraging online textual data from location-based platforms, despite providing useful information about visitors' experiences and opinions about activity locations (POIs), requires a critical perspective for several reasons.

Firstly, the reliance on user-generated content introduces a potential bias, as reviews may not represent the entire visitor range, possibly favoring individuals with stronger opinions. Additionally, these datasets lack personal information, hindering the possibility of relating preferences and experiences with specific demographic characteristics. Moreover, such data are primarily collected for commercial purposes and may lack the depth and objectivity required for detailed research.

While existing literature has extensively utilized online textual data from social media platforms such as TripAdvisor to analyze visitors' experiences and preferences, there are limitations to using such data, for instance, potential biases due to lack of user representativeness and lack of personal information. To address these limitations, it becomes critical to complement these data sources with more focused primary data collection efforts through surveys, incorporating both self-reported geographical location-based data and detailed visitor background information from a representative sample. This suggests a mixed method approach of combining opportunistic data sources (i.e., social media) with solicited data (i.e., surveys), which allows a more detailed and targeted analysis and, therefore, should generate deeper knowledge of visitor behavior and preferences in urban heritage tourism.

2.3. Revisit Intention

The close relationship between revisit intentions and a visitor's perception and experience during a stay has been explored in tourism studies, involving how individuals or communities interpret and make sense of their environment, with experiences consisting of the actual interactions and encounters individuals have with the overall tourism destination [52]. These factors are important, as positive experiences and a strong emotional connection emerge as influential on revisit intention.

Several key factors influence visitors' behavior toward repeat visits to a destination, including visitors' pleasure and perceived quality [53,54], maintenance and cleanliness of the site [55], and visitors' previous experience [56,57]. Visitors often express happiness and pleasure by returning to the same destination or recommending the site to others [58]. The more positively tourists perceive a destination, the greater the chance they will revisit it or suggest it to others because perceptions of the destination's image play a key role in tourists' decision making and subsequent travel choices [42,59–61].

These perceptions are shaped by multi-layered destination attributes related to attractions, infrastructure, environment, and service quality [62]. Consequently, satisfied tourists are more inclined to revisit a destination and recommend it to others [63]. The evidence indicates that experiences, the physical attributes of the destination, environmental quality, and satisfaction are all important factors influencing the likelihood of recommendation, the intention to revisit, and a destination's image.

Several studies [21–23] emphasize the influence of travel group composition on visitors' satisfaction levels and their intention to revisit. The study of Bigné et al. [21] distinguishes emotional-based segments related to enjoyment of leisure and tourism services in response to interactive museum (tourist context) and theme park (local context) visits. Their study uncovers two different segments, namely a group that feels less emotion (pleasure, arousal) and a group that feels more emotion. Members of the group experiencing greater pleasure and arousal experience greater satisfaction and have more positive behavioral intentions; in other words, they are willing to pay more and show more loyalty.

The study of Campo-Martinez et al. [22] analyzes the influence of group composition in terms of travel party (including traveling alone, with a partner, as a family with children, and with friends) on repeat visits to Mallorca. This study highlights that there is a strong association between the likelihood of revisiting the island and the segment of "family with children", which is mediated by a positive satisfaction level. Within a segment, different individuals may perceive varying levels of overall satisfaction and a desire to revisit. Therefore, understanding tourists' behavior and overall satisfaction with the destination and its attributes is important. Strategies for attracting different types of travelers depending on the travel party (i.e., alone, traveling with friends) can be tailored to address the motivations and needs of each segment rather than using a standardized approach.

The existing studies reviewed above present evidence of the importance of distinguishing visitor profiles in the analysis of preferences and destination choice. The integration of user-generated content from location-based social network data such as TripAdvisor provides an advancement. Yet, given the potential bias of these data, visitors' self-reported personal and location data could further improve reliability. Existing studies emphasize overall visitor satisfaction and revisit intention; however, it is also critical to examine these aspects at the POI level regarding segment-based intra-destination dynamics. Considering factors at the more detailed location level could yield more fine-grained knowledge of visitor location choice behavior, which is important for refining destination management strategies in the context of urban heritage tourism.

3. Methodology

In this section, we explain the case area, survey design, and methods used to analyze the data for identifying visitors' segments, their spatial choice behavior, and revisit intentions in this study.

3.1. Case Area

In this study, we selected Amsterdam as our case area. Tourism is an integral part of the Dutch economy, and it generated a total added value of EUR 31.8 million in 2019. However, due to COVID-19-related restrictions, this number dropped by EUR 16.5 million in 2020 but rebounded to EUR 19 million in 2021. Before the restrictions, approximately nine million guests stayed overnight in accommodations in Amsterdam within a year, followed by Rotterdam (1.2 million), The Hague (1 million), and Utrecht (449.000) [64]. These numbers reveal an imbalance in tourist distribution across major Dutch cities. Amsterdam, in particular, is home to more than 7500 heritage sites that contribute to the city's cultural and historical identity. The historic city center, with its iconic canal belt, holds UNESCO World Heritage status [65]. Amsterdam was selected as the focus of this study due to its increasing number of tourists and exceptional heritage value, with the aim to understand visitors' spatial choice behavior and their revisit intentions.

3.2. Survey Design

For this study, we collected data through an online survey which was designed to understand respondents' visited locations and their experiences at the visited locations on a recent visit to Amsterdam. The questionnaire included questions to gather respondents' sociodemographic characteristics, inquiries about their most recent visit to Amsterdam with a focus on urban heritage tourism, and statements exploring respondents' motivations related to the various benefits associated with heritage visits. Furthermore, a stated choice experiment was conducted to measure visitors' preferences for specific attributes of heritage locations and their surrounding environments. Additionally, we used an interactive map-based approach, supplemented by a series of questions to assess respondents' location choices, perceptions, and experiences during their most recent trip. Figure 1 shows an image of this interactive map-based part of the questionnaire.

The map interface allowed respondents to indicate the locations they visited, and their experiences related to these visited locations. This section of the survey provides information about respondents' actual location choices and corresponding experiences. Respondents were provided with a map of Amsterdam and asked to identify the most memorable and significant places they visited during their last trip. Respondents could zoom in and out on the map to select a specific place that left a memorable impression. Following the selection of each location, respondents were prompted to rate it using a 5-point Likert Scale on various perceptual aspects. The items included the acceptability of the experienced level of crowdedness, satisfaction regarding the level of maintenance, safety, and cleanliness, the intention to revisit the location in the future, and the recommendation of the visited place to others.

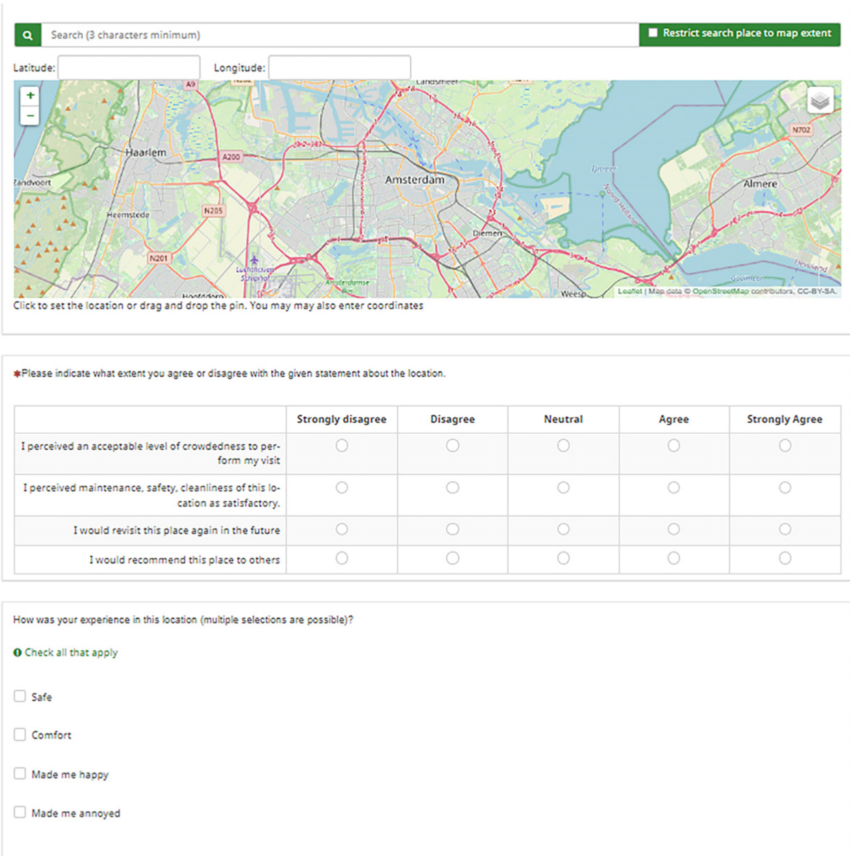

Figure 1. The interactive map-based part of the questionnaire.

3.3. Latent Class Analysis of Stated Choice Experiment Data

To identify segments in terms of preferences for attributes of heritage locations, the Stated Choice Experiment (SCE) was implemented as part of the online survey. In this experiment, respondents are presented hypothetical alternatives about heritage locations that were varied on several attributes. The respondents were asked to indicate their choice based on the attributes of each location alternative. Each respondent received nine such choice tasks. The attributes varied in the experiment covered different aspects of heritage locations and information about experiences of other visitors. These included heritage category (commercial or governmental heritages, cultural or educational heritages, recreational heritages), historical urban landscape value (HUL) [66] (architecture, urban, nature), entrance fee (EUR 0, 20, 40), the availability of pre-visit information (mobile application, website, no available information), the availability of other heritage sites and facilities within walking distance (heritage sites present, hotel/café/restaurants present, no heritage sites or other facilities present), the perceived attractiveness by other visitors (3-star, 2-star, 1-star), the overall evaluation of other visitors (very good, good, average), and perceived crowdedness level by other visitors (not crowded, moderately crowded, very crowded).

The stated choice experiment and the results of latent class analysis are described in detail by Karayazi et al. [67]. In this present study, we will use the three visitor segments identified in Karayazi et al. [67], each representing a specific segment, with corresponding membership probabilities. Based on the preference patterns, the classes were labeled by the authors as "cultural-attraction seekers" (49%), "selective sightseers" (27%), and "city-life lovers" (24%).

For the present study, the class an individual belongs to provides an explanatory variable for the (revealed) location choices that are of interest. To indicate preferences displayed by the classes, the relative importance value assigned to attributes in each class, as derived from the utility estimates, is shown in Table 1. The figures in Table 1 represent the magnitude of utility difference between the most and least preferred levels, which indicates the importance of the attribute in location choice; the wider the utility range, the stronger the influence of the attribute. In the table, "All classes (base)" represents the attribute importance score based on the Multinomial Logit (MNL) estimation results. This category shows the average importance value across all segments. Considering all classes, it appears that the entrance fee is the most important attribute in urban heritage location choice, followed by, in order of decreasing importance, the perceived average crowdedness by other visitors, the perceived heritage attractiveness by other visitors, heritage category, other heritages and facilities within walking distance, overall evaluation of other visitors, HUL, and the availability of pre-visit information.

Table 1. Attribute importance in base and latent class models.

Attributes	All Classes (Base)	LC1	LC2	LC3
Constant	1.159	2.480	0.532	2.918
Heritage category	0.352	0.373	0.555	0.432
Historical urban landscape values	0.159	0.187	0.257	0.550
Entrance fee	1.477	0.445	2.970	5.065
Availability of pre-visit information	0.071	0.125	0.218	0.275
The availability of other heritages and facilities within walking distance	0.290	0.228	0.364	1.031
Perceived heritage attractiveness by other visitors	0.440	0.450	0.905	0.299
Overall evaluation of other visitors	0.175	0.171	0.275	0.595
Perceived average crowdedness level by other visitors	0.523	0.427	1.086	0.332

The first segment (LC1), labeled "cultural-attraction seekers", involves individuals who prefer visiting cultural attractions while avoiding crowded places. Their location choices strongly depend on the attractiveness of heritage sites, and they are willing to pay for experiences and attractions. The second segment (LC2), labeled "selective sightseers", also tends to avoid crowded areas and is attracted to culturally significant heritage sites. However, they are less inclined to pay entrance fees for visiting heritage locations. They place high value on others' opinions regarding destination attractiveness. Furthermore, they have a relatively high base reference for not choosing a location from the available options, indicating that they are more critical in terms of what is offered. The third segment (LC3), labeled "city-life lovers", prioritizes urban experiences and city life. Crowdedness is not important for these individuals, and they highly value the availability of other heritage sites and facilities in the near environment.

3.4. Revealed Data Structure and the Characterization of Spatial Segments

For the purpose of identifying the connections between Points of Interest (POIs) and specific visitor segments, a multifaceted approach was adopted. Considering the research objective, our focus was on the attraction of top tourist locations in Amsterdam. Therefore, we extracted a list of the top 100 attractions and activities in Amsterdam from TripAdvisor, focusing specifically on those attractions that are recommended as "Things to Do in Amsterdam" [68]. The full list of selected POIs is represented in Appendix A.

To identify the POIs associated with the reported locations by survey respondents, 'the distance to nearest hub' algorithm was used. Hereby, the POIs were set as origins and the top 100 things to do in Amsterdam from TripAdvisor were set as destinations. Thus, the POI related to each reported location was identified as the closest POI from the top 100 POIs of TripAdvisor. This approach provided the data necessary for the subsequent application of the Association Rule Mining (ARM) method, a powerful data mining and rule-based machine learning technique introduced by Agrawal and Srikant [69]. ARM identifies patterns in data, enabling the determination of rules that define co-occurrence relations among items of interest [70–73]. In this research, we are interested in the associations between the classes and POIs visited. The well-known Apriori algorithm is used to generate the association rules based on the data.

Applied to our case, the association rules can be defined formally as follows. The given transaction dataset V contains a set of locations $\left[\, V_i,\ \left\{L_p, \ldots,\ L_q\right\}\right]$, where V_i is a unique location identifier and each location is described by POIs A with levels L_A in the form of $[L_i,\ description]$, where $A_i \in I$ (for $i = p, \ldots, q$). A rule has the form of $X => Y$ (if X then Y), where $X, Y \subseteq A$ and $X \cap Y\ \neq$. X is called the antecedent (left-hand side or LHS) and Y the consequent (right-hand side or RHS) of the rule. In this context, L associated with each location in the dataset includes information about the POI and the class of the individual visiting that location.

Key concepts for the identification of association rules are support, confidence, and lift [74]. Minimum levels of support and confidence are set to establish thresholds for rules. Setting the thresholds too low can result in the generation of numerous associations that lack statistical significance. On the other hand, setting the thresholds too high incurs a risk of not identifying meaningful rules [72].

Support measures the frequency of a specific itemset (combination of items) in the dataset, in our case a specific combination of class of the person and POI. High support indicates that the itemset is frequent in the dataset. Formally, support is defined as:

$$Support\ (X \to Y) = \frac{Number\ of\ transactions\ with\ both\ X\ and\ Y}{Total\ number\ of\ transactions} = P(X \cap Y) \tag{1}$$

where P is occurrence probability.

Confidence quantifies the reliability of an association rule. This measure represents the likelihood that, given the presence of one item, another item will also be present. A rule with a high confidence value is considered reliable. The confidence value is defined as:

$$Confidence\ (X \to Y) = \frac{Number\ of\ transactions\ with\ both\ X\ and\ Y}{Total\ number\ of\ transactions\ X} = \frac{P(X \cap Y)}{P(X)} \tag{2}$$

Lift indicates how much more likely two items occur together compared to what would be expected if they were independent. It is defined by the confidence of the rule divided by the expected confidence under the assumption of independence. Thus, the lift value helps to identify whether an association between items is significant or random. In our case, this measure can highlight meaningful correlations between class and POI visited. A lift value equal to 1 indicates a zero correlation, a lift value greater than 1 is a positive correlation, and a lift value smaller than 1 is a negative correlation. The expected confidence and lift ratio are defined as:

$$Expected\ Confidence\ (X \to Y) = \frac{Number\ of\ transactions\ with\ \ Y}{Total\ number\ of\ transactions} = P(Y) \tag{3}$$

$$Lift\ (X \to Y) = \frac{Confidence\ (X \to Y)}{Expected\ Confidence\ (X \to Y)} = (P(X \cap Y))/(P(X)\ \times\ P(Y)) \tag{4}$$

The result of ARM is complemented by spatial density maps (see Section 4.3) that provide insights into the relations between visitor segment and places visited in Amsterdam. The results provide support for strategic decision making for managing visitor flows and enhancing visitors' experience in the city.

4. Results

In this section, we describe the data collection, the sample characteristics, and the results of association rule mining and logistic regression analysis of revisit intentions.

4.1. Data Collection and Sample

The survey was executed through an online platform called LimeSurvey. Invitations to participate in this survey were sent to a random sample of a national panel in the Netherlands in December 2022. Ethical approval for the survey was granted by the Ethical Committee at Eindhoven University of Technology (ERB2022BE40). Participation in the survey was limited to individuals who had visited Amsterdam within the last five years. A total of 546 responses were gathered. Incomplete or inconclusive surveys were excluded from the analysis. Furthermore, locations indicated by respondents falling beyond the administrative boundaries of the municipality of Amsterdam were excluded. A total of 1280 location observations from 320 respondents remained for the association rule and regression analysis (see Figure 2).

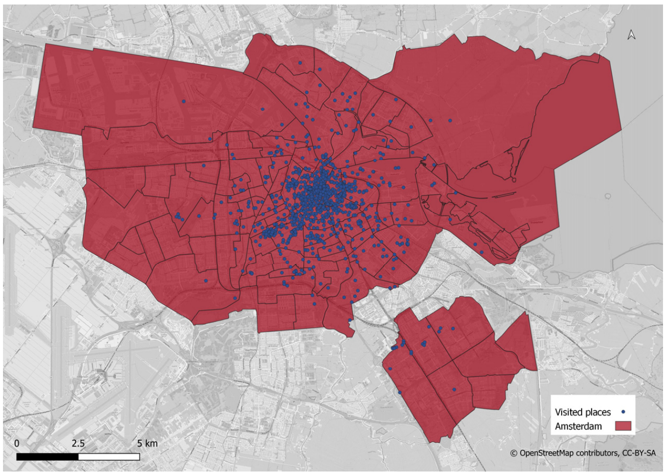

Figure 2. Reported locations by respondents.

The sample characteristics are presented in Table 2. The sample has approximately an equal representation of male and female respondents. As for the age group, the sample is skewed towards younger adults, which may reflect the nature of the study's target group of visitors to Amsterdam. A significant portion of respondents hold higher education degrees, and they tend to have a higher level of formal education. All income groups are represented in the sample, albeit the low-income group is relatively small. Half of the respondents have full-time employment.

Table 2. Sample characteristics (N = 1280).

Variable	Category	All Classes (%)	LC1 (%)	LC2 (%)	LC3 (%)
Gender	Male	48.1	48.3	57.0	51.9
	Female	51.9	51.7	43.0	48.1
Age	18–34 years	33.4	33.8	32.6	33.7
	35–54 years	37.8	36.4	33.7	46.6
	55 years or older	28.7	29.8	33.7	21.7
Education	Low education	8.8	8.6	5.8	12.0
	Middle education	41.6	43.0	44.2	36.1
	High education	49.7	48.3	50.0	51.8
Income	<EUR 20.000	9.4	7.3	12.8	9.6
	EUR 20.000–50.000	48.1	49.7	48.8	44.6
	>EUR 50.000	34.1	33.1	31.4	38.6
	Prefer not to answer	8.4	9.9	7.0	7.2
Occupation	Full-time (>32 h)	50.0	47.7	48.8	55.4
	Part-time (<32 h)	21.9	22.5	23.3	19.3
	Other	28.1	29.8	27.9	25.3

The breakdown into classes shows that there are no big differences in the distribution of the sociodemographic variables between classes, although there are some differences. Selective sightseers (LC2) are distinct in terms of a slight male majority and a relatively even age distribution. City-life lovers (LC3) stand out with a high proportion of persons in the highly educated group.

4.2. Descriptive Statistics of Class

Table 3 shows descriptive statistics of trips related to the last visits of respondents to Amsterdam within five years. A total of 75.9% of the respondents visited the city for a one-day trip, and respondents' main purpose was a city trip (84.4%). Most respondents traveled together with others (87.5%). The other travel parties were family members including children (20.9%), colleagues (3.8%), friends (28.1%), or others (3.4%). Most respondents traveled together with one other person (52.2%). The distribution of travel days is relatively balanced between weekends (51.9%) and weekdays (44.1%). In terms of season, a considerable number of respondents chose summer (40.6%) and spring (28.1%). Most people indicated that a car (54.7%) or public transport (43.8%) was used for the trip to Amsterdam. For traveling within Amsterdam, walking was chosen most often (60.6%) followed by public transport (25.6%). A total of 47.8% of the respondents indicate that they visited heritage sites and were aware of the heritage value.

Table 3. The distributions of last visit variables per class (N = 1280).

Variable	Category	All Classes (%)	LC1 (%)	LC2 (%)	LC3 (%)
Number of day(s)	Multiple days	24.1	33.1	10.5	21.7
	One day	75.9	66.9	89.5	78.3
Purpose	City trip	84.4	86.8	82.6	81.9
	Other	15.6	13.2	17.4	18.1
Travel party (alone)	No	87.5	88.7	89.5	83.1
	Yes	12.5	11.3	10.5	16.9
Travel party (family-only adult)	No	50.3	45.0	54.7	55.4
	Yes	49.7	55.0	45.3	44.6
Travel party (family including children)	No	79.1	76.8	76.7	85.5
	Yes	20.9	23.2	23.3	14.5
Travel party (colleagues)	No	96.3	97.4	94.2	96.4
	Yes	3.8	2.6	5.8	3.6
Travel party (friends)	No	71.9	74.2	75.6	63.9
	Yes	28.1	25.8	24.4	36.1
Travel party (others)	No	96.6	97.4	95.3	96.4
	Yes	3.4	2.6	4.7	3.6
Number of people (including respondent)	Alone	8.8	7.3	9.3	10.8
	2	52.2	55.0	48.8	50.6
	3	15.3	16.6	20.9	7.2
	4+	23.8	21.2	20.9	31.3
Travel days	Full week	4.1	6.0	0.0	4.8
	Weekdays	44.1	43.7	50.0	38.6
	Weekends	51.9	50.3	50.0	56.6
Travel season	Fall	21.9	17.9	26.7	24.1
	Spring	28.1	30.5	29.1	22.9
	Summer	40.6	43.0	37.2	39.8
	Winter	9.4	8.6	7.0	13.3
Initial travel mode to Amsterdam	Car	54.7	64.2	40.7	51.8
	Other	1.6	1.3	3.5	0.0
	Public transportation	43.8	34.4	55.8	48.2

Table 3. *Cont.*

Variable	Category	All Classes (%)	LC1 (%)	LC2 (%)	LC3 (%)
Travel mode within Amsterdam	Car	10.3	13.2	4.7	10.8
	Other	3.4	2.6	7.0	1.2
	Public transportation	25.6	28.5	20.9	25.3
	Walking	60.6	55.6	67.4	62.7
Heritage awareness	Did not visit (no aware)	27.5	20.5	32.6	34.9
	No (aware but did not visit)	24.7	23.8	25.6	25.3
	Yes (aware and visit)	47.8	55.6	41.9	39.8

The distributions of the last visit variables show some differences between classes. The cultural attraction seekers (LC1) are distinct in terms of the dominance of family-only adult travel parties. The selective sightseers (LC2) stand out with a high proportion of individuals who use public transport as their mode of transportation for the trip to Amsterdam.

4.3. Association Rules

This section aims to identify the associations between POIs and visitor segments. There are no commonly agreed standards for setting threshold levels for support and confidence. *Support* indicates how often a specific combination of items such as the class of the person and type of POI occurs in the dataset. Higher support indicates a greater frequency of the item set. *Confidence* represents the reliability of a rule by measuring the probability that one item accompanies the other. A high confidence value indicates high reliability. *Lift* indicates the degree of association between two items, helping to identify significant associations between class and type of POI visited.

Raising the minimum support threshold limits the number of association rules discovered but may filter out potentially valuable rules with lower support [75]. Low-support rules, in particular, may be of interest because they tend to be more innovative [76]. The "arules" and "arulesviz" R packages were used to conduct the Association Rule Mining (ARM) method. Several iterations were used to determine suitable thresholds. Ultimately, the minimum degree of support was set to 0.01, the minimum confidence level to 0.20, and the minimum lift value to 0.50. The minimum degree of support was set to a relatively low value in order to find novel rules. These parameter settings resulted in a total of 81 rules describing associations between POIs and latent classes. These rules were sorted in descending order of lift score. The full list of rules can be found in Appendix B.

Table 4 shows the five association rules having the highest lift and meeting minimum values for support and confidence, for each class. These rules provide insights into the POIs that are most strongly associated with a specific class. Support, confidence, and lift values provide valuable metrics for evaluating the strength and significance of these associations.

Rule 1 shows that there is a strong association between the "Molen van Sloten" POI and cultural attraction seekers (LC1), with a confidence of 1.00. This indicates that visitors of this POI consistently fall into the LC1 class. Similar strong associations of this class are observed with "Museum Het Rembrandthuis" and "Begijnhof", suggesting that visitors to these places are highly likely to belong to LC1. Selective sightseers (LC2) display a strong association with "Rijksmuseum", with a lift of 2.66. The POIs "Tropenmuseum", "Ge Gooyer Windmill", "Ripley's Believe It or Not", and "Centraal Station" are also strongly associated with LC2, as indicated by relatively large lift values. City-life lovers (LC3) demonstrate a strong association with the "Dutch National Opera Ballet," as indicated by the lift value of 2.75. Furthermore, "Museum Het Rembrandthuis", "Artis Zoo", "Youseum Amsterdam", and "Tropenmuseum" are POIs that are strongly associated with LC3.

Table 4. The top five association rules of visited POIs per class.

Rules_ID	Rules	Support	Confidence	Lift
1	{X3_POI_name=Molen van Sloten} => {Class=LC1}	0.01	1.00	2.12
7	{X2_POI_name=Museum Het Rembrandthuis} => {Class=LC1}	0.02	1.00	2.12
15	{X2_POI_name=Begijnhof} => {Class=LC1}	0.02	1.00	2.12
13	{X1_POI_name=St. Nicholas Basilica} => {Class=LC1}	0.02	0.83	1.77
3	{X4_POI_name=De Bijenkorf} => {Class=LC1}	0.01	0.80	1.70
27	{X3_POI_name=Rijksmuseum} => {Class=LC2}	0.02	0.71	2.66
37	{X1_POI_name=Tropenmuseum} => {Class=LC2}	0.01	0.50	1.86
43	{X2_POI_name=Ge Gooyer Windmill} => {Class=LC2}	0.01	0.50	1.86
95	{X2_POI_name=Ripley's Believe It or Not} => {Class=LC2}	0.02	0.50	1.86
109	{X4_POI_name=Centraal Station} => {Class=LC2}	0.02	0.46	1.72
29	{X4_POI_name=Dutch National Opera Ballet} => {Class=LC3}	0.02	0.71	2.75
39	{X3_POI_name=Museum Het Rembrandthuis} => {Class=LC3}	0.02	0.63	2.41
33	{X4_POI_name=Artis Zoo} => {Class=LC3}	0.01	0.50	1.93
97	{X3_POI_name=Youseum Amsterdam} => {Class=LC3}	0.02	0.50	1.93
139	{X4_POI_name=Tropenmuseum} => {Class=LC3}	0.02	0.47	1.80

Figure 3 shows the density of visited POIs on a map of Amsterdam for all classes (Figure 3a), cultural attraction seekers (Figure 3b), selective sightseers (Figure 3c), and city-life lovers (Figure 3d). In this visualization, lift values per class are plotted. Hence, the intensities in the maps show the location choices that are strongly associated with the respective class. Darker red areas represent larger lift values, while brighter areas indicate smaller values. The most frequently visited locations across classes (see Figure 3a), such as Madame Tussauds, Begijnhof, and The Jordaan, are located in the historical core of Amsterdam. Other frequently visited POIs across classes are clustered around Vondelpark and Museum Quarter. A general observation is that the distribution of locations related to cultural attraction seekers extends to more peripheral locations in contrast to selective sightseers and city-life lovers.

As can be seen in Figure 3b, cultural attraction seekers exhibit a preference for museums including Museum Het Rembrandhuis, Youseum Amsterdam, The National Maritime Museum, and Madame Tussauds. Additionally, they extend their visits to the opposite shore of the IJ river to visit the International Straat Art Museum and Wondr Experience. Cultural attraction seekers are often composed of younger individuals who may travel with children and opt for a car, signifying an interest in family-friendly and flexible experiences [67]. This explains the dispersed distribution of the locations they visit, as their favored locations are accessible by car. Conversely, it may be that they opt for car transportation because they intend to visit these specific locations. Possibly, attractions such as Wondr Experience, with its indoor playground designed for adults and accompanying children in surreal, colorful rooms created by artists, align well with their preferences for family-friendly attractions. Other chosen locations include attractions such as St. Nicholas Basilica and the Dutch National Opera Ballet.

Selective sightseers (Figure 3c), on the other hand, exhibit a preference for more central locations compared to the other classes. Firstly, these individuals demonstrate a distinct interest in Amsterdam Centraal Station and exhibit a strong affinity for parks, such as Vondelpark and Artis Zoo. These individuals often belong to an older age group, tend to travel in smaller groups, and are less inclined to travel by car [67]. Their spatial preference is consistent with their preference for alternative transportation modes that offer local travel experiences. These location preferences align with the association to Amsterdam Centraal Station, which provides access to various transportation modes, including tram and metro, facilitating travel over short distances.

City-life lovers (Figure 3d) present a more compact spatial visiting pattern compared to other classes. With the only exception of Youseum Amsterdam, the locations they visit tend to cluster around the city center and are in proximity to Amsterdam Centraal Station.

Among the locations typically chosen by this class are museums such as Museum Het Rembrandhuis, Youseum Amsterdam, and Tropenmuseum.

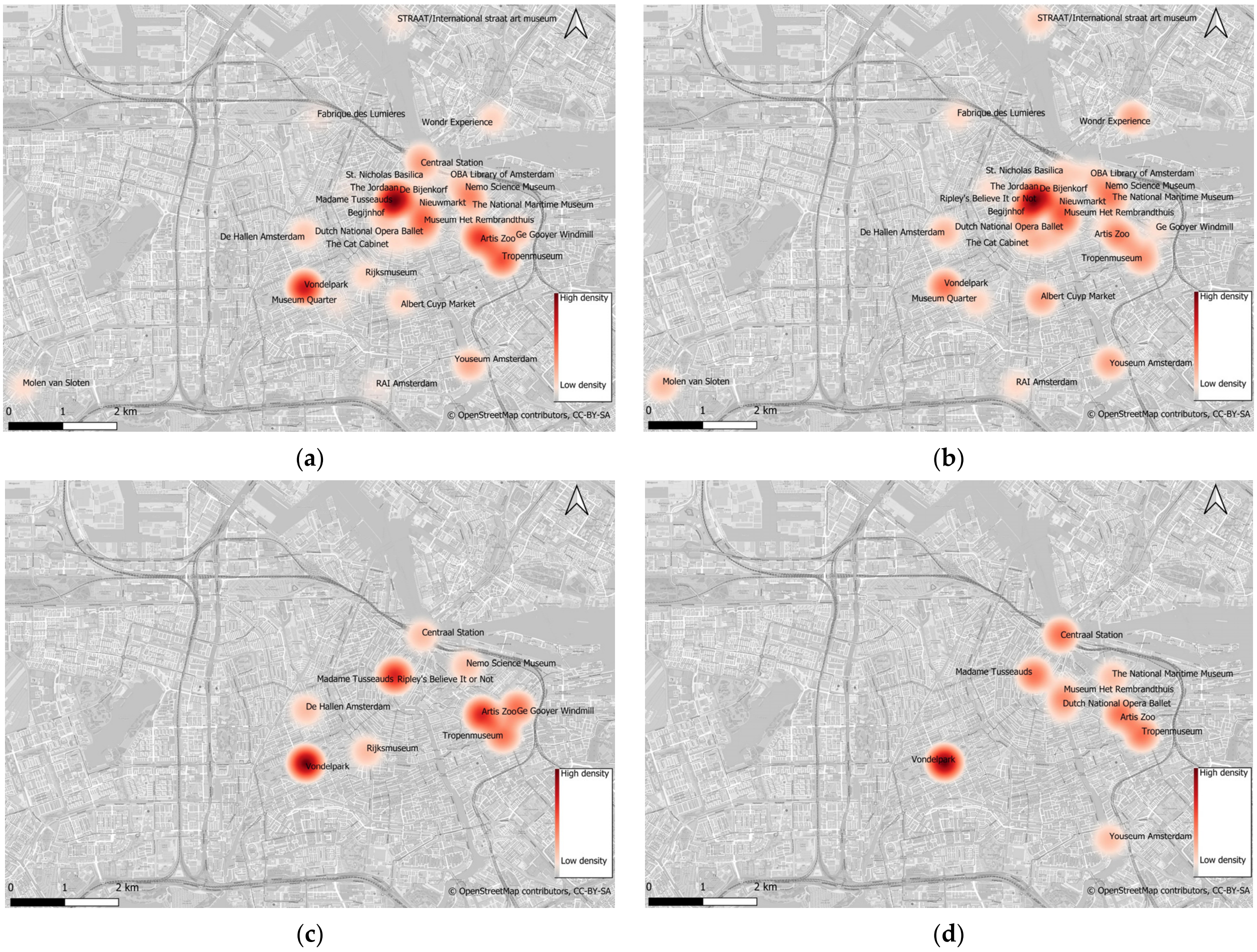

Figure 3. Spatial segmentation of visited POIs across different visitor classes: (**a**) all classes; (**b**) cultural attraction seekers (LC1); (**c**) selective sightseers (LC2); (**d**) city-life lovers (LC3).

4.4. The Influence of Visitors' Experiences on Their Revisit Intentions

A Binary Logistic Regression analysis was conducted to estimate the relation between revisit intention and visitors' experiences associated with reported location visits. Since our interest lies in determining whether these reported locations will be revisited in the future, the revisit intention responses were transformed into a binary variable (see Table 5). Responses to the statement 'I would revisit this place again in the future' of "agree" (4) and "strongly agree" (5) were classified as 1 (yes) and "neutral" (3), "disagree" (2), and "strongly disagree" (1) were classified as 0 (no).

Table 5. The responses of revisit intention (N = 1280).

	The Distribution of Revisit Intention				
ordinal	1 16	2 75	3 338	4 632	5 219
binary	0	0 429	0	1	1 851

The regression model accurately classified 82.7% of the cases. This is a considerably higher rate compared to the null model (66.5% correct), indicating the accuracy of the model in predicting the correct intention category based on the included predictors. The Nagelkerke Rho-square of 0.49 indicates a satisfactory fit of the model.

Table 6 shows the estimation results. Experiences such as safety, comfort, happiness, and annoyance were binary variables indicating whether respondents selected these experiences as applicable. Perceptions of crowdedness, satisfaction, and recommendation were coded according to the rating on a 5-point scale by respondents and assumed to approximate an interval measurement level.

Table 6. Results of the binary logistic model.

	β	*p*-Value	Exp (β)
safe	0.269	0.135	1.309
comfort	0.479	0.006	1.615
happy	0.743	<0.001	2.102
annoyed	1.271	<0.001	3.566
crowdedness	0.195	0.092	1.215
satisfaction	0.515	<0.001	1.674
recommend	1.843	<0.001	6.317
city-life lovers	0	0.118	0
cultural attraction seekers	0.328	0.070	1.389
selective sightseers	0.382	0.073	1.465
Constant	−9.502	<0.001	0.000

Variable(s) entered on step 1: safe, comfort, happy, annoyed, crowdedness, satisfaction, recommend, latent classes.

The experience of happiness and annoyance and the perceived satisfaction level and recommendation all have a significant positive effect on revisit intention at a 1% significance level. These variables are positively associated with the likelihood of revisiting. Visitors who reported feeling comfort in the reported location are 1.6 times more likely to express an intention to revisit. Similarly, visitors who reported feeling happy are 2.1 times more likely to revisit, while those who reported feeling annoyed are 3.6 times more likely to have this intention. Although it could be expected that positive experiences like comfort and happiness increase the likelihood of revisiting, the positive effect of annoyance on revisit intention is unexpected. One possible explanation is that the initial visit may not have met the visitors' expectations because it was negatively affected by specific conditions such as the timing of the initial visit leading to consideration of returning later.

The coefficient for the variable "perceived acceptable level of crowdedness" has a positive value, indicating that an increase in perceived crowdedness is associated with a higher likelihood of revisiting. The reason could be that some visitors perceive a destination as more attractive when it is crowded. They might connect crowdedness with popularity and view it positively. Additionally, some visitors might have unique preferences and intentionally seek crowded destinations to enjoy social interactions. However, this effect is statistically significant only at the 10% level. The odds ratio is 1.215, indicating that a 1-point increase in crowdedness results in a 21.5% higher likelihood of revisiting.

The variables "perceived satisfactory level of maintenance, cleanliness and safety" and "recommendation the visited location to others" both have positive coefficients and are significant at the 1% level. For a 1-point increase in "perceived satisfactory level of maintenance, cleanliness and safety", the odds of revisiting increase by a factor of approximately 1.7. Higher satisfaction is associated with a 67.4% higher likelihood to revisit. Similarly, for a 1-point increase in "recommendation the visited location to others", the odds of revisiting increase substantially by a factor of 6.3. These findings suggest that overall satisfaction and the intention to recommend a location are strong indicators of revisit intention.

The model also includes pre-defined latent classes (city-life lovers, cultural attraction seekers, selective sightseers) as predictor variables. For the estimation, class is treated as a categorical covariate and "city-life lovers" is taken as the base level. The effect of "cultural attraction seekers" is significant at the 10% level (p = 0.07); visitors belonging to this group are 1.4 times more likely to revisit than "city-life lovers". "Selective sightseers" have a similar tendency, with a p-value of 0.073 and an odds ratio of 1.465, suggesting that they are more likely to revisit compared to "city-life lovers".

5. Conclusions and Discussion

This study aimed to achieve two primary objectives: (i) to identify the relationships between visitor segments and tendencies to choose particular POIs on a historical city trip, and (ii) to analyze the impacts of visitors' experiences and visitor segments on revisit intentions. The analysis was conducted using a sample of individuals who have visited Amsterdam within the past five years.

The study provides a comprehensive analysis of respondents' experiences and preferences during their visit to Amsterdam. In terms of spatial distribution, "cultural attraction seekers" exhibited a preference for locations that are spatially dispersed, potentially favorable for family-friendly experiences. These locations may continue to draw future crowds, especially if they maintain or enhance their appeal to families. "Cultural attraction seekers" are likely to revisit Amsterdam's cultural attractions and they may continue to explore new locations and museums, making them repeat visitors. Past studies suggest that visitors who habitually return to a destination they have previously visited tend to exhibit consistent behavior in their future visits. Their preferences and actions during subsequent visits are likely to follow a pattern based on their past choices [42,58,61].

Conversely, "selective sightseers" displayed a preference for more central locations and relied on local transportation modes for their travel experiences. They are likely to revisit central attractions and parks, potentially leading to consistent future crowds at these central locations. This finding aligns with previous studies by Girardin et al. [77] and van der Zee et al. [32], indicating that tourists tend to gravitate towards central locations. They are less likely to explore peripheral locations but might continue to enjoy central attractions, parks, and local transportation options for short-distance trips.

City-life lovers, on the other hand, exhibited a more compact distribution pattern, with a noticeable preference for specific museums at central locations, which may continue to attract this group. This class might contribute to future crowds concentrating in the core of Amsterdam, particularly around Amsterdam Centraal Station and the museums in the city center.

Experiences play an important role in influencing future crowds, as visitors who associate positive experiences with a place are more likely to revisit it, which could contribute to crowding at these locations. Contrary to expectations, encountering negative emotional experiences, such as annoyance, does not necessarily reduce the visitors' intention to revisit the destination [60]. However, it is essential to acknowledge that while experiences are a factor, they are not the sole determinants of future visit patterns. Other factors, such as events [30], accessibility, and trends, also shape future visit patterns.

This study used mixed methods, utilizing online surveys to collect data from a geographically diverse group, whereby the random selection of participants aids in reducing sample bias. The combination of Association Rule Mining (ARM) to understand preferences among POIs and spatial segmentation for visualizing the preferences of different visitor segments contributes to identifying visitors' location choice behavior. Binary Logistic Regression was used to analyze the relationship between revisit intentions and visitors' experiences attached to reported locations. The analysis shows that visitors who feel happy or annoyed, are highly satisfied, and are more likely to recommend the location to others express a higher likelihood of revisit intention.

The analysis of revealed data provides knowledge about the actual choices and spatial behavior of visitors. This serves as the base for the distinction of visitor segments and facilitates the exploration of the relationship between these segments and POIs. This contributes to understanding how various groups of visitors interact with and prioritize distinct locations within Amsterdam. To address potential issues related to future crowding, the authorities of Amsterdam could implement strategies such as crowd control measures, timed entry systems, promotion of off-peak visits, and diversification of attractions to evenly distribute visitors across the city based on the spatial patterns exhibited by the different visitor segments. For "Cultural Attraction Seekers", who tend to favor museums, family-friendly experiences, and accessible locations by car, authorities could promote off-peak visits to these cultural sites and museums. Moreover, diversifying attractions in the peripheral areas, where these seekers tend to concentrate, might aid in distributing visitors more evenly across the city.

In contrast, "Selective Sightseers" prefer more central locations, particularly around Amsterdam Centraal Station. Authorities could implement timed entry systems at central attractions to facilitate smoother crowd management. Additionally, encouraging the use of alternative transportation modes for local travel experiences might be beneficial for this segment. For "City Life Lovers", who exhibit a more clustered pattern in the city center, authorities could focus on optimizing the city center's attractions to accommodate their preferences. Strategies could include promoting diverse activities in the city center to ensure that it remains an attractive and engaging destination.

Despite the valuable insights gained from this study concerning visitors' experiences and their impact on revisit intentions, as well as the identification of the relationship between POIs and pre-defined visitor segments, several limitations should be acknowledged. Firstly, the selection of POIs relies on TripAdvisor's database, which may be influenced by users' ratings and subject to change due to the dynamic nature of the web platform. Secondly, the choice of thresholds for ARM (e.g., support, confidence, and lift) can significantly affect the number and quality of association rules generated, rendering the selection of appropriate thresholds a challenging task.

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Appendix A

Table A1. Things to do in Amsterdam.

ID	POI	ID	POI	ID	POI	ID	POI
1	Anne Frank House	26	OBA Library of Amsterdam	51	St. Nicholas Basilica	76	Our House Museum
2	Van Gogh Museum	27	Amsterdam Canal Ring	52	De Poezonboot	77	Haarlemmerstraat
3	Rijksmuseum	28	Molen van Sloten	53	Singel	78	Amsterdam Tulip Museum

Table A1. *Cont.*

ID	POI	ID	POI	ID	POI	ID	POI
4	Vondelpark	29	Rembrants Amsterdam Experience	54	Leidseplein	79	Rtxp Amsterdam
5	The Jordaan	30	Portuguese Synagogue	55	Wondr Experience	80	Magere Brug
6	Centraal Station	31	De 9 Straatjes	56	De Hallen Amsterdam	81	The Cat Cabinet
7	Heineken Experience	32	Albert Cuyp Market	57	Tropenmuseum	82	Amsterdam Tourist Ferry
8	Museum Ons' Lieve Heer Op Solder	33	Dutch National Opera Ballet	58	Koninklijk Theater Carre	83	Damrak
9	Body Worlds	34	The Amstel	59	Fabrique des Lumieres	84	Westerpark
10	Red Light District	35	Amsterdamse Bos	60	Eye Film Institute	85	Foam-Photography Museum Amsterdam
11	Artis Zoo	36	De Duif	61	Hash Marihauna and Hemp Museum	86	Nieuwmarkt
12	Museum Het Rembrandthuis	37	Tour de BonTon	62	Museum van Loon	87	Ge Gooyer Windmill
13	Verzetsmuseum Amsterdam	38	Stadelijk Museum	63	Amsterdam Pipe Museum	88	Vincent Meets Rembrandt
14	A'dam Lookout	39	Rembrandtplein	64	De Bijenkorf	89	RAI Amsterdam
15	Dam Square	40	Hermitage Amsterdam	65	Amsterdam Museum	90	Buiksloterweg Ferry
16	Moco Museum Amsterdam	41	Ripley's Believe It or Not	66	Westerkerk	91	Anne Frank, Her Diary on Stage
17	Museum Quarter	42	Joods Historic Museum	67	Brouwersgracht	92	Brouwerij de Prael
18	Royal Palace Amsterdam	43	Johan Cruyff Arena	68	Museum Vrolik	93	Bridge of 15 Bridges
19	Begijnhof	44	Keizergracht	69	Amstelpark	94	Huis Bartolotti
20	The National Maritime Museum	45	Museum of the Canals	70	Museum Hep Schip	95	Munttoren
21	Micropia	46	Hortus Botanicus	71	Noordermarkt	96	Cannabis College
22	Nemo Science Museum	47	Willet-Holthuysen Museum	72	Houseboat Museum	97	Zeedijk
23	Madame Tusseauds	48	Youseum Amsterdam	73	De Krijtberg	98	King's day
24	GWB	49	Ziggo Dome	74	STRAAT/International straat art museum	99	Theater Amsterdam
25	Herengracht	50	Museum of Prostitution	75	Hema	100	Concertgebouw

Appendix B

Table A2. The association rules of visited POIs and pre-defined classes.

Rules_ID	Rules	Support	Confidence	Lift
29	{X4_POI_name=Dutch National Opera Ballet} => {Class=LC3}	0.02	0.71	2.75
27	{X3_POI_name=Rijksmuseum} => {Class=LC2}	0.02	0.71	2.66
39	{X3_POI_name=Museum Het Rembrandthuis} => {Class=LC3}	0.02	0.63	2.41
1	{X3_POI_name=Molen van Sloten} => {Class=LC1}	0.01	1.00	2.12
7	{X2_POI_name=Museum Het Rembrandthuis} => {Class=LC1}	0.02	1.00	2.12
15	{X2_POI_name=Begijnhof} => {Class=LC1}	0.02	1.00	2.12
33	{X4_POI_name=Artis Zoo} => {Class=LC3}	0.01	0.50	1.93
97	{X3_POI_name=Youseum Amsterdam} => {Class=LC3}	0.02	0.50	1.93
37	{X1_POI_name=Tropenmuseum} => {Class=LC2}	0.01	0.50	1.86
43	{X2_POI_name=Ge Gooyer Windmill} => {Class=LC2}	0.01	0.50	1.86
95	{X2_POI_name=Ripley's Believe It or Not} => {Class=LC2}	0.02	0.50	1.86
139	{X4_POI_name=Tropenmuseum} => {Class=LC3}	0.02	0.47	1.80
13	{X1_POI_name=St. Nicholas Basilica} => {Class=LC1}	0.02	0.83	1.77
109	{X4_POI_name=Centraal Station} => {Class=LC2}	0.02	0.46	1.72
69	{X3_POI_name=Centraal Station} => {Class=LC3}	0.01	0.44	1.71
3	{X4_POI_name=De Bijenkorf} => {Class=LC1}	0.01	0.80	1.70
5	{X2_POI_name=Youseum Amsterdam} => {Class=LC1}	0.01	0.80	1.70
9	{X1_POI_name=The Cat Cabinet} => {Class=LC1}	0.01	0.80	1.70
59	{X4_POI_name=STRAAT/International straat art museum} => {Class=LC1}	0.02	0.78	1.65
113	{X1_POI_name=Nemo Science Museum} => {Class=LC2}	0.02	0.43	1.59
123	{X1_POI_name=Madame Tusseauds} => {Class=LC2}	0.02	0.43	1.59
41	{X3_POI_name=Albert Cuyp Market} => {Class=LC1}	0.02	0.75	1.59
151	{X1_POI_name=Artis Zoo} => {Class=LC2}	0.03	0.42	1.57
83	{X1_POI_name=The National Maritime Museum} => {Class=LC3}	0.01	0.40	1.54
85	{X4_POI_name=Ripley's Believe It or Not} => {Class=LC3}	0.01	0.40	1.54
25	{X4_POI_name=Museum Quarter} => {Class=LC1}	0.02	0.71	1.51
111	{X4_POI_name=Wondr Experience} => {Class=LC1}	0.03	0.71	1.51
75	{X3_POI_name=Ge Gooyer Windmill} => {Class=LC2}	0.01	0.40	1.49
145	{X1_POI_name=Ripley's Believe It or Not} => {Class=LC1}	0.03	0.69	1.46
11	{X1_POI_name=Begijnhof} => {Class=LC1}	0.01	0.67	1.41
17	{X4_POI_name=Madame Tusseauds} => {Class=LC1}	0.01	0.67	1.41
19	{X2_POI_name=OBA Library of Amsterdam} => {Class=LC1}	0.01	0.67	1.41
49	{X1_POI_name=Museum Het Rembrandthuis} => {Class=LC1}	0.02	0.67	1.41
55	{X3_POI_name=Tropenmuseum} => {Class=LC1}	0.02	0.67	1.41
57	{X3_POI_name=The National Maritime Museum} => {Class=LC1}	0.02	0.67	1.41
63	{X1_POI_name=Bridge of 15 Bridges} => {Class=LC1}	0.02	0.67	1.41
121	{X1_POI_name=Madame Tusseauds} => {Class=LC3}	0.02	0.36	1.38
91	{X3_POI_name=Madame Tusseauds} => {Class=LC2}	0.01	0.36	1.35
47	{X3_POI_name=Dutch National Opera Ballet} => {Class=LC1}	0.02	0.63	1.32
163	{X4_POI_name=Vondelpark} => {Class=LC3}	0.02	0.33	1.29
71	{X2_POI_name=Verzetsmuseum Amsterdam} => {Class=LC1}	0.02	0.60	1.27
73	{X3_POI_name=RAI Amsterdam} => {Class=LC1}	0.02	0.60	1.27
81	{X3_POI_name=Fabrique des Lumieres} => {Class=LC1}	0.02	0.60	1.27
99	{X1_POI_name=Nieuwmarkt} => {Class=LC1}	0.02	0.58	1.24
21	{X1_POI_name=Hash Marihauna and Hemp Museum} => {Class=LC1}	0.01	0.57	1.21
23	{X1_POI_name=Wondr Experience} => {Class=LC1}	0.01	0.57	1.21
31	{X4_POI_name=Albert Cuyp Market} => {Class=LC1}	0.01	0.57	1.21
101	{X2_POI_name=Tropenmuseum} => {Class=LC3}	0.01	0.31	1.19
107	{X4_POI_name=Centraal Station} => {Class=LC3}	0.01	0.31	1.19
51	{X2_POI_name=The Jordaan} => {Class=LC1}	0.02	0.56	1.18
61	{X3_POI_name=Nemo Science Museum} => {Class=LC1}	0.02	0.56	1.18
65	{X3_POI_name=De Hallen Amsterdam} => {Class=LC1}	0.02	0.56	1.18
67	{X2_POI_name=The National Maritime Museum} => {Class=LC1}	0.02	0.56	1.18

Table A2. *Cont.*

Rules_ID	Rules	Support	Confidence	Lift
173	{X2_POI_name=Vondelpark} => {Class=LC1}	0.05	0.56	1.18
103	{X2_POI_name=Tropenmuseum} => {Class=LC2}	0.01	0.31	1.14
149	{X3_POI_name=Artis Zoo} => {Class=LC1}	0.03	0.53	1.12
153	{X1_POI_name=Artis Zoo} => {Class=LC1}	0.03	0.53	1.12
157	{X2_POI_name=Artis Zoo} => {Class=LC3}	0.02	0.29	1.10
147	{X3_POI_name=Artis Zoo} => {Class=LC2}	0.02	0.29	1.09
117	{X4_POI_name=De Hallen Amsterdam} => {Class=LC2}	0.01	0.29	1.06
45	{X2_POI_name=Madame Tusseauds} => {Class=LC1}	0.01	0.50	1.06
77	{X3_POI_name=Ge Gooyer Windmill} => {Class=LC1}	0.02	0.50	1.06
79	{X4_POI_name=Youseum Amsterdam} => {Class=LC1}	0.02	0.50	1.06
87	{X4_POI_name=Ripley's Believe It or Not} => {Class=LC1}	0.02	0.50	1.06
119	{X4_POI_name=De Hallen Amsterdam} => {Class=LC1}	0.02	0.50	1.06
127	{X1_POI_name=Vondelpark} => {Class=LC3}	0.01	0.27	1.03
133	{X3_POI_name=Vondelpark} => {Class=LC3}	0.01	0.27	1.03
161	{X2_POI_name=Artis Zoo} => {Class=LC1}	0.03	0.48	1.01
129	{X1_POI_name=Vondelpark} => {Class=LC2}	0.01	0.27	0.99
135	{X3_POI_name=Vondelpark} => {Class=LC2}	0.01	0.27	0.99
131	{X1_POI_name=Vondelpark} => {Class=LC1}	0.02	0.47	0.99
137	{X3_POI_name=Vondelpark} => {Class=LC1}	0.02	0.47	0.99
115	{X1_POI_name=Nemo Science Museum} => {Class=LC1}	0.02	0.43	0.91
167	{X4_POI_name=Vondelpark} => {Class=LC1}	0.03	0.43	0.91
159	{X2_POI_name=Artis Zoo} => {Class=LC2}	0.02	0.24	0.89
165	{X4_POI_name=Vondelpark} => {Class=LC2}	0.02	0.24	0.89
169	{X2_POI_name=Vondelpark} => {Class=LC3}	0.02	0.22	0.86
141	{X4_POI_name=Tropenmuseum} => {Class=LC1}	0.02	0.40	0.85
171	{X2_POI_name=Vondelpark} => {Class=LC2}	0.02	0.22	0.83
105	{X2_POI_name=Tropenmuseum} => {Class=LC1}	0.02	0.38	0.82
93	{X3_POI_name=Madame Tusseauds} => {Class=LC1}	0.01	0.36	0.77

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