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Article

Using Wi-Fi Probes to Evaluate the Spatio-Temporal Dynamics of Tourist Preferences in Historic Districts' Public Spaces

Yichen Gao [1,2,3], Sheng Liu [1,2,*], Biao Wei [1,2], Zhenni Zhu [1,4] and Shanshan Wang [1]

1 School of Art and Archaeology, Hangzhou City University, Hangzhou 310015, China; gaoyc@hzcu.edu.cn (Y.G.); 221122150160@zjut.edu.cn (Z.Z.); 2231003010@stu.hzcu.edu.cn (S.W.)
2 Zhejiang Provincial Cultural Institute for Grand Canal, Hangzhou 310015, China
3 College of Civil Engineering and Architecture, Zhejiang University, Hangzhou 310058, China
4 School of Design and Architecture, Zhejiang University of Technology, Hangzhou 310023, China
* Correspondence: lius@hzcu.edu.cn

Abstract: Tourist preferences for public spaces in historic districts can reflect whether renovated spaces and functional structures meet tourism demands. However, conventional big data lack the spatio-temporal accuracy needed to support a refined, dynamic study of small-scale public spaces inside historic districts. This paper, therefore, proposes using a Wi-Fi probe to evaluate the spatio-temporal dynamics of tourists' spatial preferences in historic districts. We conducted a one-week measurement in the Xiaohe Street Historic Block in Hangzhou, China. Three indicators—visit time preference, aggregation preference, and stay preference—were used to examine the dynamic change in tourists' spatial preferences, with 15 min as the time unit and public spaces with a radius of 25 m as the spatial unit. Our research demonstrates that, compared with conventional big data, the Wi-Fi probe offers a more reasonable and accurate method to measure tourists' spatial preferences in historic districts at a smaller time and spatial granularity. The research findings can be applied to evaluate the effectiveness of spatial regeneration and diagnose renewal-related issues in historic districts. It can also serve as a foundation for more precise planning of public spaces in historic districts, as well as the modification of functional structures.

Keywords: Wi-Fi probe; tourist preference; spatio-temporal dynamics; small public spaces; historic districts

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1. Introduction

Since the establishment of the first batch of National Famous Historic and Cultural Cities in 1982, China has focused on the protection and renewal of historic districts. The protection of historic districts was formally proposed during the designation of the second batch of National Famous Historic and Cultural Cities in 1986. Since then, many historic districts have undergone spatial renewal and incorporated tourism functions, becoming new tourist destinations. However, the effectiveness of historic district renewal has not been sufficiently evaluated, and methods for carrying out evaluations pose certain challenges. Since historic districts involve multiple stakeholders, including residents, businesses, district managers, and the government, different parties have different views about the effectiveness of historic district renewal. As for tourist development in a district, the perspective of tourists is the most direct one. Tourist preferences regarding public spaces in historic districts can directly reflect whether transformed public spaces meet tourism needs. This can help diagnose issues with the renewal of public spaces in a district and provide a reference for further revitalization and enhancement.

Most current studies of tourists' spatial preferences are focused on larger scales, mainly at the level of a city or an entire scenic area, with historic districts often being considered simply as tourist destinations within a city [1,2]. Historic districts, however, have complex spatial compositions that include various special elements, such as cultural heritage, historic architecture, and public spaces. Research on a micro-scale regarding tourists' spatio-temporal behavior within these districts is still relatively limited. The existing literature fails to fully elucidate tourists' preferences for small-scale spaces in historic districts and their interactions with the environment. Given the global trend towards historic district conservation and renovation, the micro-renewal of small-scale spaces has become the preferred approach. This underscores the importance of accurate evaluation for these spaces.

Questionnaires and interviews continue to be the primary research methodologies used in small-scale studies on tourist preferences. Jiang and Liu distributed questionnaires to locals and tourists in a historic district to discover each group's perception of cultural landscapes [3]. Poruțiu et al. conducted a questionnaire survey of tourists in a rural tourist destination in Romania to better understand their tourism behavior and attractiveness of the destination [4]. Such methods typically capture only static preferences and possess limitations when evaluating tourist preferences dynamics. The advancements in information and IoT technologies have opened up new possibilities for studying human behavior and spatial form at finer spatio-temporal scales [5]. In recent years, numerous tourist tracking technologies that can be adapted to different spatial scales have been developed. Wi-Fi data, in particular, offer new opportunities for measuring tourist behavior in small-scale spaces [6]. This content will be explored in detail in Section 2.

In summary, while there is a lack of dynamic, small-scale research on tourist preferences in historic districts, advancements in new technologies have created new opportunities for these studies. Consequently, this study aims to explore a quantitative approach for dynamically evaluating tourists' preferences that applies to small public spaces in historic districts. We introduced Wi-Fi probe technology to analyze tourists' spatio-temporal behaviors in these areas by interpreting their visit time preference, aggregation preference, and stay preference. Our study offers a quantitative, cost-effective approach to data collection, processing, and analysis, facilitating a tourist-centric examination of spatial and tourism issues in historic districts. The research findings can serve as a foundation for the precise governance of public spaces within historic districts.

2. State of the Art

Benefiting from the development of information and communication technologies (ICTs), diverse tourist tracking techniques provide rich data support for quantitative studies on tourism behavior at various spatial scales. Currently, commonly used tourist tracking techniques include social media, mobile networks, tourism market transaction data, GPS, and Wi-Fi [7]. Among these, social media, mobile networks, and tourism market transaction data were often used to study tourism behavior at large geographic scales. For instance, geo-tagged social media data from platforms such as Twitter, Instagram, Flickr, Dianping, etc., can help identify popular tourist attractions and potential destinations in cities or scenic areas [8–11]. Mobile network data are often used to segment tourist types and explore patterns of travel movement between or within destinations [12].

However, the spatial resolution, timeliness, coverage, and specificity of this type of big data or open data are often insufficient [13], and the data access threshold is quite high, limiting its use in micro-scale spaces. Recently, active urban sensing based on sensors and Internet of Things (IoT) technologies [13] is increasingly being utilized in related research to compensate for the spatial and temporal inaccuracies of conventional big data. For example, Zhang et al. combined a handheld GPS tracking device and a questionnaire survey to explore the spatio-temporal behavioral patterns of tourists in a botanical garden [14]; Gea-García et al. utilized eye-tracking devices to analyze the visual interest points of hikers and identify more engaging tourist landscapes [15]; and Zhou et al. proposed a data analysis framework using Wi-Fi data for analyzing the spatial, temporal, and spatio-temporal patterns of tourists in an outdoor social event [16]. The emergence of active urban sensing technologies has provided more opportunities for researchers to capture complex human dynamics and their interactions with the environment in small-scale space.

As a type of active urban sensing technology, Wi-Fi data are an emerging data source for studying crowd behavior and its dynamics. Wi-Fi data collected through signals from mobile devices [17] have been utilized for crowd-tracking at multiple spatial scales, from cities to communities. For instance, Salas et al. applied Wi-Fi data to analyze urban mobility in an international tourist city [18]. Li et al. collected Wi-Fi data to identify the spatial aggregation pattern and the temporality of the tourist flow at a community tourist attraction [19]. Hu et al. used Wi-Fi data to investigate crowd activities in urban public green spaces [20].

Wi-Fi data, characterized by its high spatio-temporal granularity, can be used to collect real-time information on crowd behavior and activity patterns at specific locations. It has been primarily applied to study the aggregation patterns of crowds and their dynamics over time by counting visit numbers at specific locations [19–21]. Furthermore, it was possible to categorize crowd attributes according to the frequency of mobile device presence, allowing researchers to investigate differences in spatial distribution patterns among distinct crowds [22,23]. Another common use for Wi-Fi data was tracking movement trajectories. Individual movement trajectories can be displayed based on the appearance of the temporal sequence of the same mobile device at different probing points, facilitating the analysis of human mobility patterns [24,25]. It was also employed in tourism behavior studies to identify popular tourist routes in community-scale attractions, which would guide tourism decisions [26]. In recent years, the utilization of Wi-Fi data mining has been further advanced. Several studies have increasingly focused on the application of Wi-Fi in the analysis of crowd-staying behavior. For instance, Li et al. proposed a stay-time-based method to identify the tourism attractiveness in small-scale tourist destinations [6].

Compared to GPS devices, eye-tracking devices, and other methods that require active human involvement, no action is required on the part of the participant with Wi-Fi probes [27]. This allows for collecting a broader range of samples while minimizing disturbance to crowd behavior [28]. Additionally, Wi-Fi probes appear to be more convenient and low-cost in terms of device installation and data collection [29]. Given their high spatio-temporal accuracy, Wi-Fi probes hold significant potential for dynamically evaluating tourist preferences in small public spaces within historic districts.

3. Materials and Methods

3.1. Methods for Measuring Tourists' Spatial Preferences

This study measured tourist preferences using three indicators: visit time preference, aggregation preference, and stay preference.

1. Visit time preference

The tourist visit count during different time periods can reflect which time of day tourists prefer to visit public spaces in historic districts. For this study, we recorded the tourist visit count for each public space in the whole district per unit of time at 15 min intervals and observed the dynamic changes. Furthermore, we compared tourist visit counts on different dates to analyze the variation patterns on weekdays and weekends.

$$P_{dt} = \sum_{i=1}^{a} P_{it} \tag{1}$$

where P_{dt} is the tourist visit count of the whole district during period t of day d, with time intervals of 15 min; P_{it} is the tourist visit count at space i during period t; and a is the total number of public spaces detected.

2. Aggregation preference

The tourist visit volume of a public space within a unit of time characterizes the ability of that public space to attract tourists to aggregate. We examined tourists' aggregation preferences in two time dimensions: overall and by time interval. In the overall dimension, we statistically analyzed the average daily tourist visit count of a public space to reflect the spatial distribution pattern of tourists' overall aggregation preferences and compared different dates. Since people typically exhibit different travel patterns on weekdays and weekends, we divided the spatial pattern of overall aggregation preference into two categories—weekdays and weekends—for separate examination. The average daily tourist visit count is calculated as follows:

$$\overline{P_i} = \frac{\sum_{d=1}^{n} P_{id}}{n}, \tag{2}$$

where $\overline{P_i}$ is the average daily tourist visit count of space i, P_{id} is the total number of tourists in space i on day d, and n is the number of days of detection, with n = 5 for weekdays and n = 2 for weekends.

In the time-interval dimension, we calculated the average tourist visit counts of each public space during the same time period on different dates to illustrate the dynamic trend of changes in aggregation preferences for each space. The calculation formula is as follows:

$$P_{it} = \frac{\sum_{d=1}^{n} P_{itd}}{n}, \tag{3}$$

where P_{it} is the average tourist visit count of space i at time period t, P_{itd} is the tourist visit count of space i during time period t on day d, and n is the number of days of detection.

Furthermore, we conducted k-means clustering analysis on the calculation results to identify public spaces with similar variations in aggregation preferences. Considering that there may be large differences in tourist visit count between different spaces, to better cluster the trend of changes in aggregation preference, we first min-max normalized the data. Then, we determined the optimal k-value by calculating the silhouette coefficient using the following equation:

$$S(i) = \frac{b(i) - a(i)}{\max\{a(i), b(i)\}}, \tag{4}$$

$$S(i) = \begin{cases} 1 - \frac{a(i)}{b(i)} & if\ a(i) < b(i) \\ 0 & if\ a(i) = b(i) \\ \frac{b(i)}{a(i)} - 1 & if\ a(i) > b(i) \end{cases}$$

where $a(i)$ is the average distance between sample point i and other sample points in the same class, representing the closeness of the sample point to elements within the class, and $b(i)$ is the average distance between sample point i and all sample points in other classes, representing the dispersion of the sample point from elements outside the class. The value of $S(i)$ is between [−1, 1]; the closer it is to 1, the better the clustering effect.

3. Stay preferences

When tourists stay in a public space, it indicates that the space has certain elements that attract them to engage in sustained activities, such as leisure, social activities, and entertainment. Therefore, tourists' stay preferences can be used to determine whether a public space in a historic district can attract tourists to stay. We used the average length of stay of tourists in a public open space to characterize tourists' stay preferences. We also calculated the standard deviation of the average length of stay. A smaller standard deviation indicates a similar length of stay in a space, reflecting similarities in tourists' stay behaviors or activity types to a certain extent. Conversely, a larger standard deviation indicates greater variability in tourists' length of stay in a space, and there might be a greater variety of activity types.

$$\text{Average length of stay}: \ \overline{R_i} = \frac{1}{P_i}\sum_{m=1}^{P_i} R_{im}, \tag{5}$$

$$\text{Standard deviation}: \ \sigma_i = \sqrt{\frac{\sum_{m=1}^{p_i}\left(R_{im} - \overline{R_i}\right)^2}{n-1}}, \tag{6}$$

where $\overline{R_i}$ is the average length of stay of the crowd in space i, P_i is the total number of tourists detected in space i, and Rim is the length of stay of individual m in space i.

3.2. Study Area

We selected Xiaohe Street Historic Block as the study area. It is located in the northern part of Hangzhou, west of the Beijing–Hangzhou Grand Canal, a UNESCO World Heritage Site. This area is an important component of the cultural heritage of the Beijing–Hangzhou Grand Canal and one of the historic districts in Hangzhou that retains an intact overall traditional appearance. In 2007, Xiaohe Street underwent protection and renewal efforts while retaining its original residents, continuing the traditional cultural life of the people along the Canal. In recent years, the district has seen the emergence of new businesses such as cafes, handicraft shops, and design studios, forming a historic and cultural district integrating residential, commercial, and leisure functions and becoming a trendy destination for young people. According to Hangzhou city government statistics, the three major historic districts along the Grand Canal, including Xiaohe Street Historic Block (the other two being Qiaoxi Straight Street and Dadou Road Historic and Cultural Block), drew a total of 7,252,900 visitors in the first half of 2023.

We focused on the observation of public spaces within the core protection zone (about 3.4 hectares) of the Xiaohe Street Historic Block. The northern side of this zone is designated as the traditional townscape control area of Xiaohe Street, while the western and southern sides are residential areas, and the northeast side adjoins Xiaohe Park. After conducting a pre-field investigation in the study area, we first excluded private spaces and work zones that were difficult for tourists to access and screened out all public spaces. Then, based on the principle of maximum coverage while considering the feasibility of device installation, we selected 21 public spaces for the placement of Wi-Fi probe devices, each with a probe detection radius set at 25 m (Figure 1). In terms of public space types, the selected spaces can be categorized as follows: the district's main entrances with large open spaces (spaces 1, 4, 7, and 9; space 1 is the main entrance of the block), public spaces adjacent to historic and cultural heritages (spaces 2 and 3), public spaces with concentrated commercial facilities nearby (spaces 8, 12, and 20), waterfront spaces along the Grand Canal (spaces 13, 14, 15, and 21), courtyard spaces within the district (spaces 5, 6, and 10), and secondary entrances of the district (spaces 11, 16, 17, 18, and 19).

3.3. Data Collection and Preprocessing

3.3.1. Data Collection

We used a TZ4007Pro WI-FI probe device (iSen, Shenzhen, China) for data acquisition. This device is equipped with a built-in 4G module. When conducting outdoor data collection, it only needs to be connected to a portable charging device. With sufficient power and data volume, there is no need to provide additional Wi-Fi signals, making data collection relatively convenient. After the probe captures Wi-Fi probing requests from mobile devices, it uploads data such as device ID (MAC addresses of Wi-Fi probe devices), source MAC (MAC addresses of the transmitting ends of the Wi-Fi signals recorded by the probes, usually are mobile devices), RSSI (received signal strength indicator), and timestamp to the cloud server (Figure 2a,c). Considering research needs, device traffic, and server load, we set the data upload interval to 30 s.

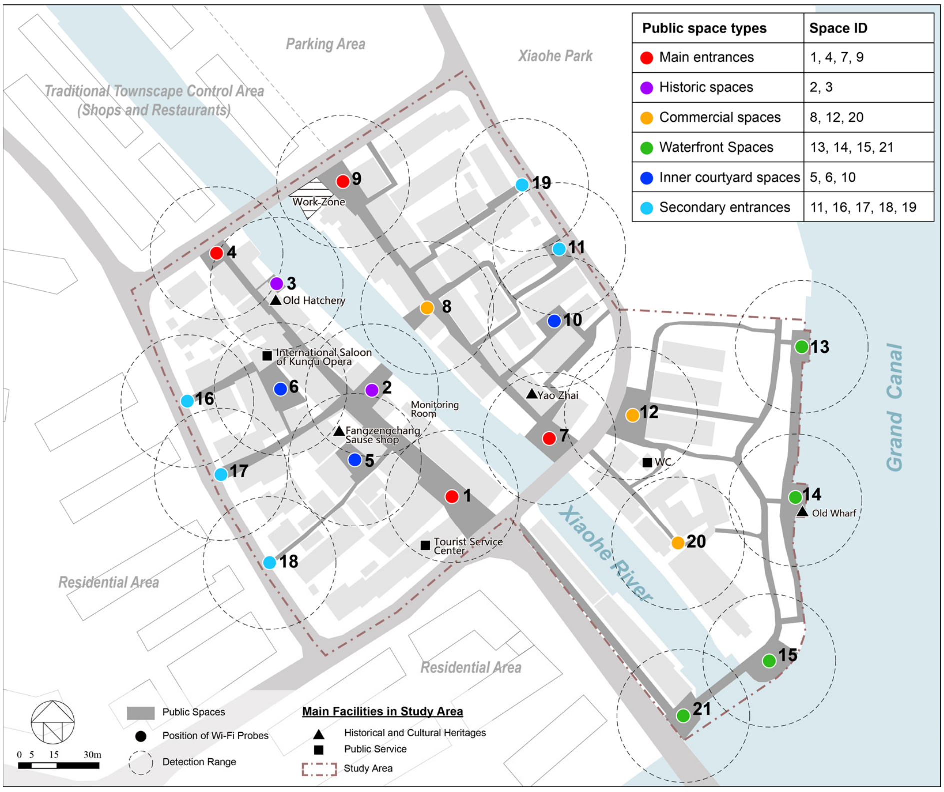
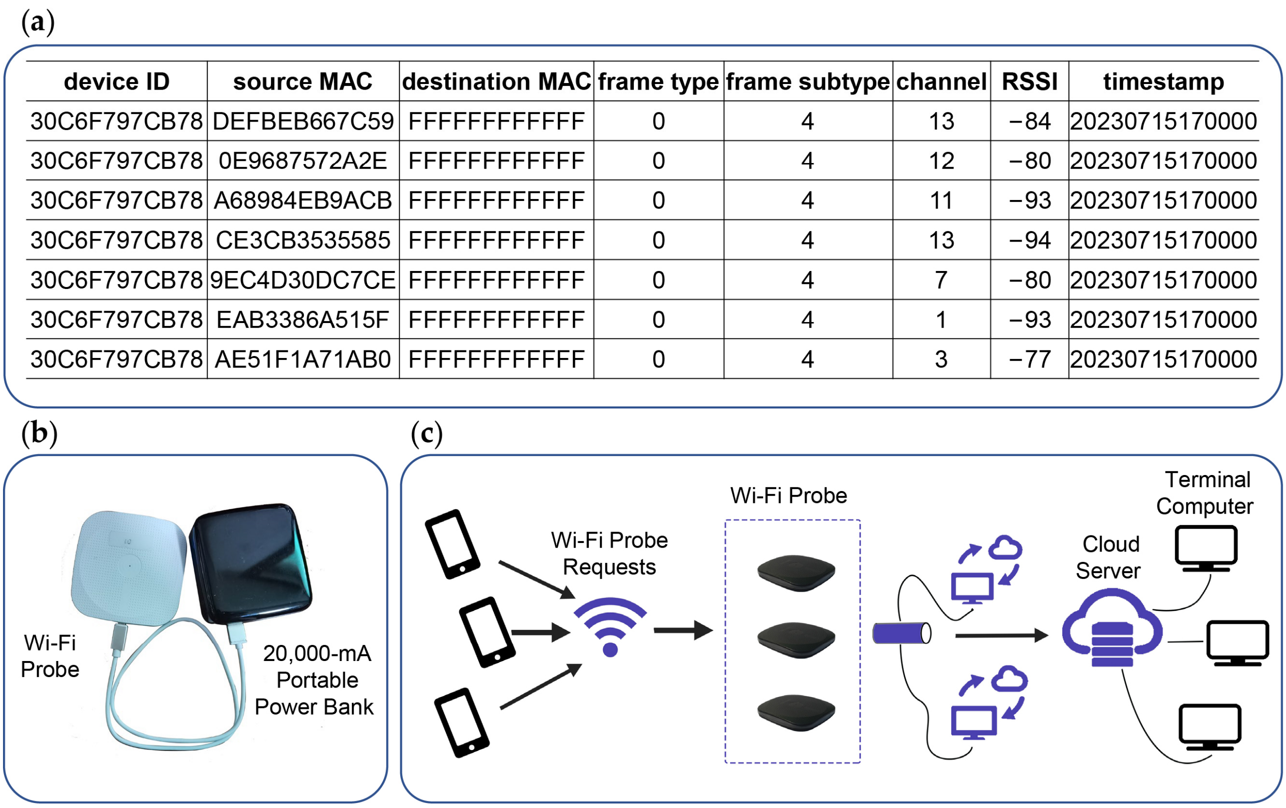


Figure 1. Public spaces in the study area and placement of Wi-Fi probes.



device ID	source MAC	destination MAC	frame type	frame subtype	channel	RSSI	timestamp
30C6F797CB78	DEFBEB667C59	FFFFFFFFFFFF	0	4	13	−84	20230715170000
30C6F797CB78	0E9687572A2E	FFFFFFFFFFFF	0	4	12	−80	20230715170000
30C6F797CB78	A68984EB9ACB	FFFFFFFFFFFF	0	4	11	−93	20230715170000
30C6F797CB78	CE3CB3535585	FFFFFFFFFFFF	0	4	13	−94	20230715170000
30C6F797CB78	9EC4D30DC7CE	FFFFFFFFFFFF	0	4	7	−80	20230715170000
30C6F797CB78	EAB3386A515F	FFFFFFFFFFFF	0	4	1	−93	20230715170000
30C6F797CB78	AE51F1A71AB0	FFFFFFFFFFFF	0	4	3	−77	20230715170000

Figure 2. (**a**) Data samples uploaded to cloud server; (**b**) assembly of Wi-Fi probes; (**c**) process of data collection.

Data were collected from 16 July 2023 (Sunday) to 22 July 2023 (Saturday) at night, with continuous monitoring conducted from 08:30 to 22:00 each day for a week, covering both weekdays and weekends. There were no special events in the district or the surrounding areas during the time period. Each probe was connected to a 20,000-mA portable power bank (Figure 2b) and adequately waterproofed, which was sufficient to support uninterrupted monitoring for a day. To ensure data-acquisition accuracy, we placed the devices in the same locations every day. During the data-acquisition period, daytime temperatures were mostly 30–35 °C, while nighttime temperatures were 28–33 °C. It was mostly sunny during the day, and there were thunderstorms lasting 30 min to one hour every early evening to nighttime. In most cases, rainfall had minimal effect on pedestrian traffic. An exception was that on the night of 19 July, Hangzhou issued a rainstorm alert, and heavy rain, to some extent, affected pedestrian travel and data collection.

3.3.2. Data Preprocessing

During the seven days of observation, we collected a total of 5,023,399 data points across the 21 spaces. To facilitate further analysis, we preprocessed the data as follows:

(1) Removal of conflicting data. Owing to potential overlaps in the Wi-Fi probe coverage areas, we assigned the MAC address of any device that was simultaneously detected by multiple probes to the node with the strongest signal strength; 4,432,459 data points remained after this step.

(2) Filtering out random MAC addresses. Random MAC addresses can influence the results when extracting tourist data and calculating stay length. Therefore, we filtered out random MAC addresses. The specific method involves examining the second character of the fourth part of the MAC address. If the character is E, A, 2, or 6, the corresponding MAC address is considered random [30]. This step removed 1,106,758 random MAC data points, accounting for 24.97% of the data.

(3) Extracting tourist data. Through a pre-investigation and considering the tourism characteristics of historic districts, it was discovered that most tourists prefer to visit for one or two days and travel around within the study area. Therefore, after filtering out passerby data that appeared only once in a single location during the data collection period, MAC addresses that appeared for 1–2 days within a 7-day period were extracted as tourist data based on their frequency. A total of 1,980,780 tourist data points were selected in this step, suggesting that tourists accounted for approximately 59.56% of the total pedestrian count.

(4) Calculating the length of stay for each individual. Using the dataset obtained in step (3), we marked the moments for each mobile device from the time it was detected by the probe at a single node to the time it left the detection range of that node. If a device was not detected for five continuous minutes, the stay behavior was considered to have ended. The next time the mobile device was detected at the same node, it was considered a second stay behavior. We calculated the length of stay for each individual by subtracting the time of leaving the space from the time of entering the space.

4. Results

4.1. Visit Time Preference

The total number of tourist visits across all spaces on weekends generally exceeded that on weekdays. However, whether on weekdays or weekends, there were fewer tourists during the morning hours, and tourists preferred to visit the public spaces on Xiaohe Street from early evening to night. Throughout the day, the overall tourist visit count showed a steady increase from daytime to nighttime, reaching its peak between 18:00 and 19:30 on all dates except July 19, when it was affected by nighttime rainstorms, followed by a decline. Compared with weekdays, there was a noticeable peak in tourist visit count in the afternoon on weekends. Most commercial and catering facilities in the district operate from 11:00 to 22:00, which aligns with the trend in tourist visit count changes, suggesting that store operating hours have a significant effect on tourist visit time preference (Figure 3).

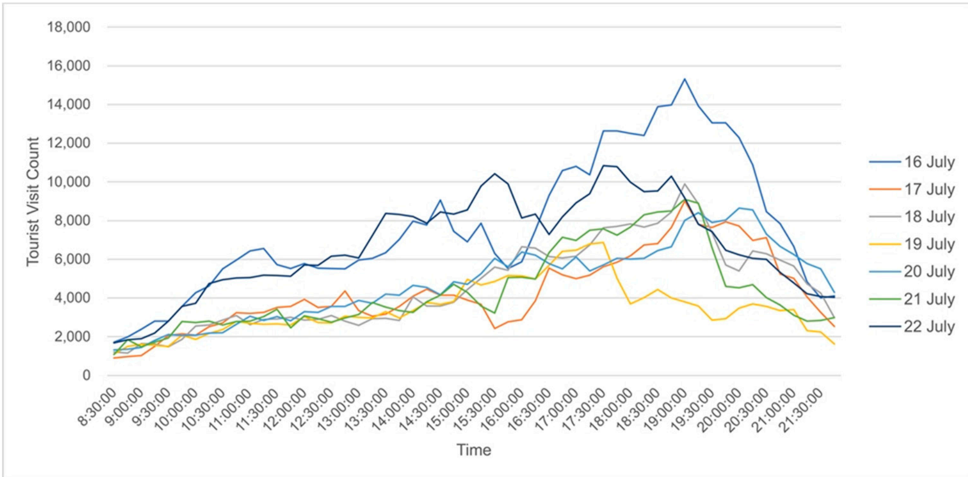


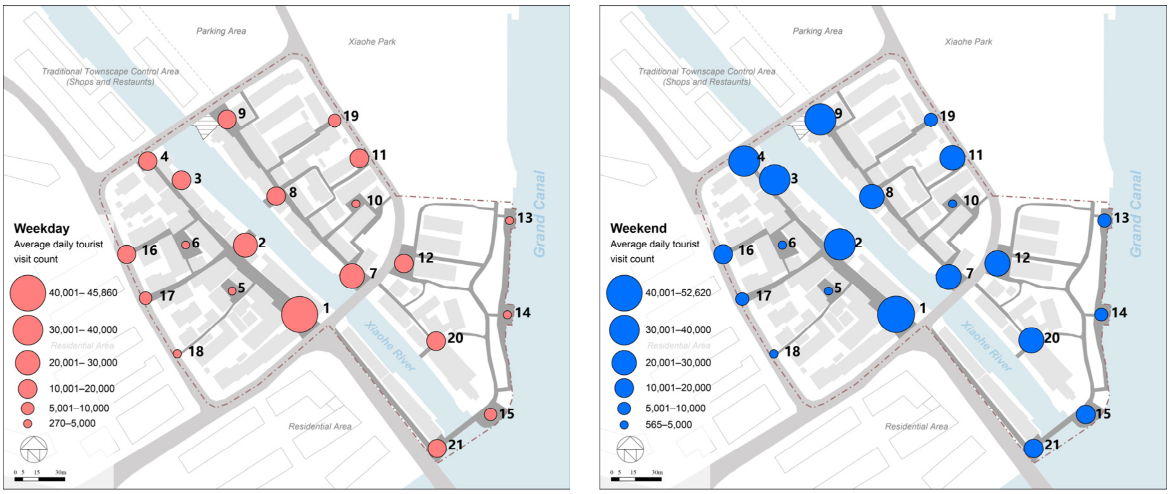
Figure 3. Trend in tourist visit count by day.

4.2. Aggregation Preference

Since the nighttime data for July 19 (Wednesday) were greatly affected by weather factors, for the sake of analysis accuracy, we excluded that day's data from the calculation of tourist aggregation preference. That is, we used n = 4 for the number of weekdays in Equations (2) and (3).

4.2.1. Overall Aggregation Preference

We measured tourists' overall aggregation preference by the average daily pedestrian visit count in each space, separately considering weekdays and weekends. There was considerable variability between spaces. In general, on both weekdays and weekends, more tourists gathered in public spaces in the district, especially those along the two main streets, than in spaces along the Grand Canal, with the highest average daily tourist visit count in space 1 (i.e., the main entrance of Xiaohe Street) and the lowest in space 6 (i.e., one of the inner courtyard spaces) (Figure 4).



(**a**) (**b**)

Figure 4. Overall aggregation preference. (**a**) Average daily tourist visit count on weekdays; (**b**) Average daily tourist visit count on weekends.

The average daily tourist visit counts in each space was generally higher on weekends, especially in spaces 3, 4, 9, 11, 12, and 20, where tourists nearly doubled on weekends compared with weekdays. The average daily tourist visit counts in space 18 showed a slight decrease on weekends, but overall, the change was not significant, indicating a similar level on weekdays and weekends (Figure 5).

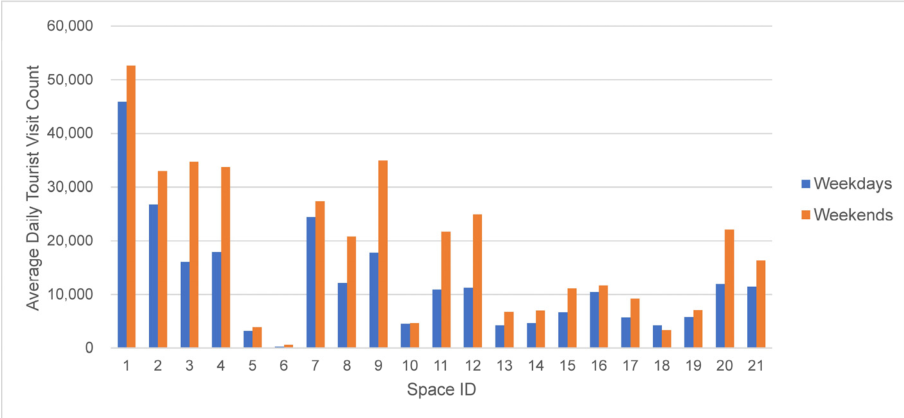


Figure 5. Average daily tourist visit count in each space on weekdays and weekends.

4.2.2. Aggregation Preference by Time Interval

We made no distinction between weekdays and weekends since they showed similar spatial distribution characteristics in terms of aggregation preference. We divided the detection time of a day into six time intervals: morning (08:30–11:00), noon (11:00–13:30), afternoon (13:30–16:00), early evening (16:00–18:30), early night (18:30–21:00), and late night (21:00–22:00). We observed tourist visit count trend in each space by statistically analyzing the average tourist visit count in the same time interval on different dates.

The analysis results revealed that the tourist visit count was basically evenly distributed in various public spaces on Xiaohe Street in the morning hours. Starting from noon, there was a trend of a large number of tourists gathering in the public spaces along the two main streets. Especially from early evening to early night, the number of tourists gathering along the main streets far exceeded that in other spaces. The tourist visit counts in the waterfront space also showed an increasing trend in the early evening, but this increase was smaller than that in the public spaces along the main streets. The tourist visit counts in the inner courtyard spaces and at the secondary entrances and exits of the district remained relatively stable throughout the day (Figure 6).

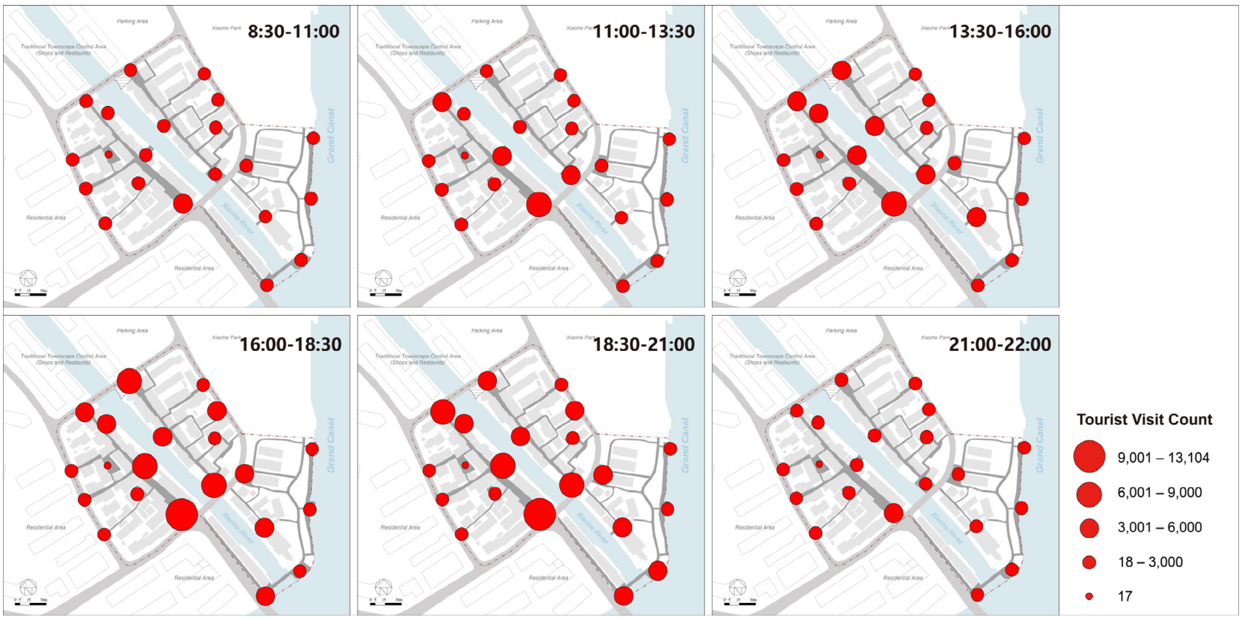
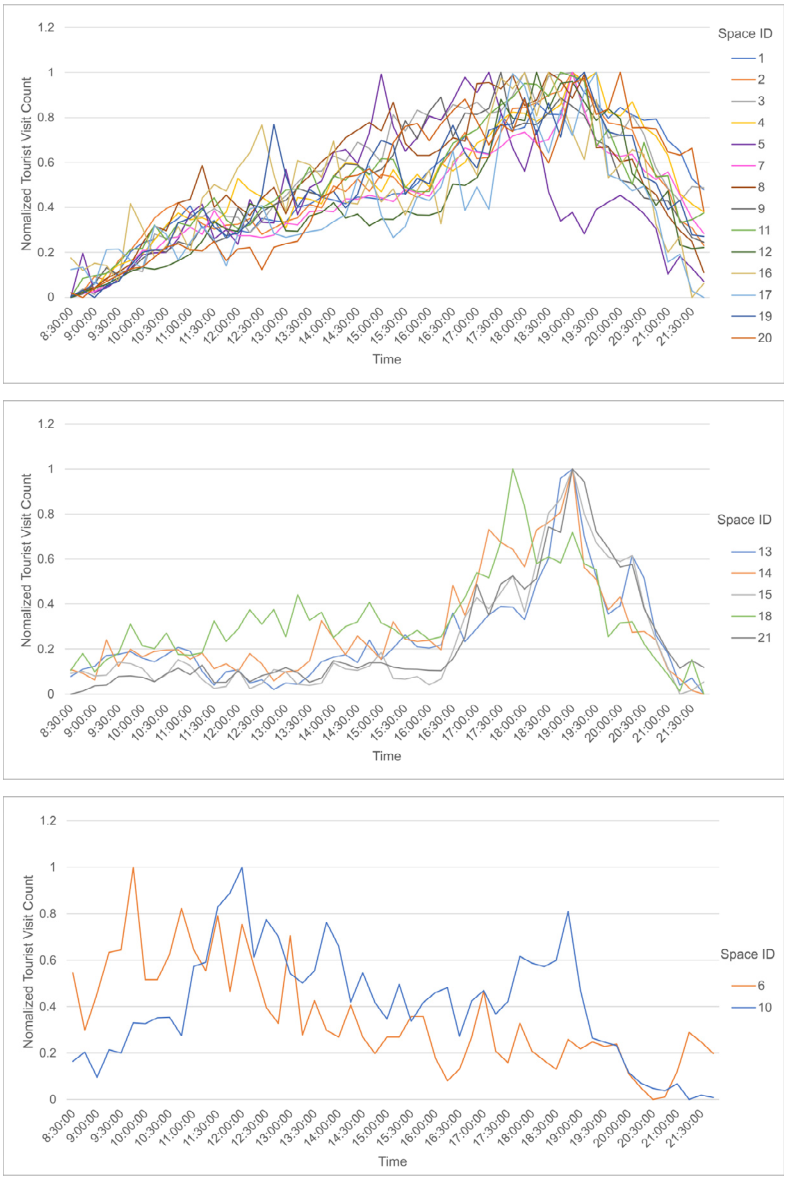


Figure 6. Tourist visit count by time interval in each space.

4.2.3. Spatial Classification Based on the Characteristics of Dynamic Changes in Aggregation Preferences

Based on the dynamic changes in aggregation preferences in each space, we performed a k-means clustering analysis on the spatial samples. From the calculation of the silhouette coefficients by Equation (4), we found that the clustering effect was the best when $k = 3$, resulting in the following three types of trends in tourists' aggregation preferences.

(1) Steady upward type. This type of public space includes the largest number of spaces—namely, spaces 1–5, 7–9, 11, 12, 16, 17, 19, and 20 (Figure 7a). The tourist visit count showed an overall steady upward trend from the start of the observation. An exception was space 19, where the tourist visit counts peaked between 18:00 and 19:30 and then gradually decreased afterward. In terms of spatial location, these public space nodes are all located within the district, mostly distributed along two main streets. In terms of public space types, main entrances and exits, historic and cultural spaces, and commercial spaces dominated, with many tourist attractions as well as commercial and catering facilities nearby.



(a)

(b)

(c)

Figure 7. Normalized tourist visit count versus time at spaces of (**a**) steady upward type, (**b**) nighttime burst type, and (**c**) no significant fluctuation type.

(2) Nighttime burst type. This type of public space includes spaces 13–15, 18, and 21 (Figure 7b). The tourist visit count in these spaces was generally relatively low with no significant increases during the day but exhibited a noticeable upward trend at night and, similar to the first type of public space, peaked between 18:00 and 19:00. This type of public space mainly consists of waterfront spaces along the Canal.

(3) No significant fluctuation type. This type of public space includes spaces 6 and 10 (Figure 7c). The tourist visit count in these spaces was consistently low throughout the day. Relatively speaking, more tourists gathered from morning to noon; there was less pedestrian traffic in the afternoon and a small peak in the evening. However, the overall change was relatively smooth, with no significant fluctuation. This type of public space consists of courtyards within the district, with fewer surrounding commercial and catering facilities and a lack of night lighting.

4.3. Stay Preferences

Observing the length of tourist stay revealed strong tourist mobility in the public spaces along Xiaohe Street Historic Block, with over 80% of tourists not staying in these spaces; that is, their stay length was 0. We then excluded data associated with a stay length of 0 and conducted analyses focusing on tourist stay behavior in these spaces by calculating the mean and standard deviation of the length of stay over all days for each space (Figure 8). We found that the mean length of tourist stay in historic and cultural spaces 2 and 3 and in waterfront spaces 13, 14, and 15 was longer than that in other spaces. The spaces with a longer length of tourist stay are typically equipped with rest facilities and have spatial elements for tourists to visit and take check-in photos. As observed from the standard deviation of stay length, there were large differences in the length of tourist stay in these public spaces, especially at nodes with complex spatial elements, such as the main entrances and exits of the district. For example, space 1 is the main entrance and exit of the district. Aside from its passing function, it also includes photo-worthy spots, such as the district sign and sculpture vignettes, as well as commercial and catering facilities nearby, such as cafes and bubble tea shops, where there were significant differences in the length of tourist stay.

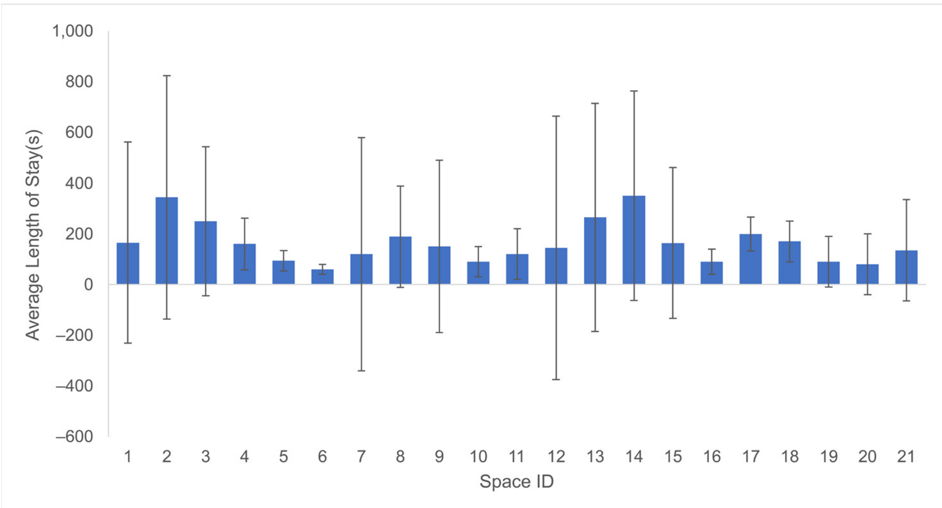


Figure 8. Average length of stay and its standard deviation at each space.

5. Discussion

Because of the lack of research on human-scale tourist preferences within historic districts and the limitations of conventional big data, this paper introduced Wi-Fi probe technology to identify tourist preferences and their dynamics in small public spaces within historic districts. This study demonstrates the practicality of using Wi-Fi probes to analyze small public spaces in historic districts while providing empirical support for evaluating tourist behaviors on a human scale. Subsequently, we will further explore the comparison with related studies, the application of research findings, and the advantages of the Wi-Fi probe-based approach.

5.1. Comparison with Related Studies

Based on the detection range of different devices and specific research needs, studies using Wi-Fi probes can configure various spatial and temporal granularities (Table 1). In previous studies, spatial granularity has been set with radii ranging from 15 m to 100 m. Our study set the spatial granularity at a radius of 25 m, considering the detection range of devices and the size of public spaces, which was the same for research conducted in community-scale settings [19,25]. In terms of temporal granularity, previous research has set time intervals ranging from 5 min to 2 h when measuring the spatial distribution dynamics of crowds. Most studies used 1 h intervals [19,22–25], which generally sufficed to capture the spatio-temporal dynamics of crowds in most scenarios. Considering the small public spaces and frequent mobility of people in historic districts (as suggested by our stay preference analysis), as well as the Wi-Fi probe's temporal accuracy, which permits finer temporal granularity, a 15 min interval was used. Using smaller temporal granularity to measure tourism behavior allows for more subtle dynamic changes in tourist preferences.

Table 1. Spatial and temporal granularities set in previous research.

Literature	Spatial Granularity	Temporal Granularity	Study Area
[16]	100 m	15 min	Waterfront
[19]	25 m	1 h	Community tourist attraction
[20]	Not mentioned	2 h	Park
[21]	Not mentioned	5 min	Metro station
[22]	75 m	1 h	Urban block
[23]	15 m	1 h	Street
[24]	75 m	1 h	Urban block
[25]	25 m	1 h	Community tourist attraction

5.2. Application of Research Findings

The research findings offer valuable insights that can be utilized to objectively evaluate the efficacy of tourism development in historic districts, guide smart changes to functional patterns, and ensure precise governance of public spaces. Using Xiaohe Street as an example, the following spatial improvement proposals are made based on the research findings.

Firstly, concerning visit time preference, it was found that tourists prefer to visit Xiaohe Street Historic Block at night. According to the field survey data, restaurants accounted for over 50% of all stores in this district, resulting in a concentration of tourists during dinner hours. This suggests the need to modify the business structure of the district. Introducing more diversified business types, such as cultural and experiential stores related to local history and culture, is recommended to attract tourists at different times of the day. Additionally, daytime utilization of public places can be enhanced by organizing activities such as flash mobs to augment travelers' experiences.

Secondly, according to aggregation preference, the aggregation of tourists in public spaces shows various dynamic characteristics, suggesting differentiated space optimization and management strategies for different types of spaces. For instance, in steady upward spaces that have relatively high visitor access throughout the day, it is recommended to manage tourist flow according to space capacity to prevent overcrowding and overtourism. In nighttime burst spaces, such as waterfront areas with fewer daytime visitors, it is recommended to install sunshades and seasonal facilities that harmonize with the surroundings to enhance the daytime tourist experience. In no-significant-fluctuation spaces, such as internal courtyards, it is recommended to add cultural experience facilities or landscape sketches related to the living culture of the Grand Canal and improve the signage system. This would attract tourists deeper into the historic district to experience the local living and cultural atmosphere, complementing the commercial-oriented tourism of the main street.

Thirdly, according to stay preference, the public space on Xiaohe Street functions more as a thoroughfare than a resting area, especially on the west side of the study area. Based on fieldwork data, spaces where tourists stay briefly are mainly the entrances and exits of neighborhoods intended for passage. These spaces should prioritize walkability to ensure smooth pedestrian flow. Other spaces lack rest facilities and have fewer photo-taking points. Therefore, these spaces can increase the length of stay by adding elements for rest and photo-taking, such as seats, landscape elements, or beautifying surrounding building façades.

5.3. Advantages of Wi-Fi Probe-Based Approach

Compared with cellular signaling data based on mobile phone signals [31,32], Wi-Fi probes have the following advantages: (1) They enable the measurement of tourist preferences for small-scale public spatial units. We set 25 m as the radius of the measurement space while distance can be determined based on the signal strength [33] so that a smaller range of the measurement space can be obtained. (2) Wi-Fi probes can capture and upload smart device probe requests in real time, enabling the dynamic measurement of tourists' spatial preferences with finer time granularity. (3) They have a lower barrier to use. The devices are low cost, easy to install, occupy minimal space, only require a stable power supply to operate continuously, are not affected by device brands or operators, and allow for a wide coverage of demographic groups (Table 2).

Table 2. Comparison of cellular signaling and Wi-Fi probes.

	Cellular Signaling	Wi-Fi Probes
Spatial accuracy	Depends on the coverage range of base stations, typically ranging from tens of meters to several kilometers; smaller radii are usually used for coverage of urban centers	Typically have a maximum measurement radius of about 25–100 m; distance can be calculated based on RSSI to define a smaller range of measurement space
Temporal accuracy	User-initiated behavioral records variable time intervals; periodic location updates, generally every 1–2 h	Real-time data capture, accurate to the second
Barriers to use	Needs to be purchased from operators or data service providers, which is expensive; data between operators are not interoperable, making it necessary to purchase from multiple operators to obtain all data	Low-cost equipment and easy to install; received data are not affected by mobile device brands or operators
Applicable scenario	Research at the urban scale	Research at the human scale

6. Conclusions

Tourism plays an important role in revitalizing historic districts. Understanding tourists' preferences is essential for evaluating the effectiveness of tourism development and diagnosing renewal-related issues in these areas. However, current research on tourist preferences in historic districts lacks dynamic tracking of tourists in small-scale public spaces. To address these gaps, we proposed a Wi-Fi probe-based framework for data collecting, processing, and analysis to identify the spatio-temporal dynamics of tourists' visit time preference, aggregation preference, and stay preference. The main contribution of this study is enhancing the temporal and spatial granularity in tourism behavior research within historic districts. Our study demonstrated that using the Wi-Fi probe-based approach, it was possible to achieve a dynamic analysis of tourist preferences for public spaces in historic districts with a spatial accuracy of 25 m radius and a temporal accuracy of 15 min. This research offers an effective method for precise spatial evaluation and supports the development of targeted spatial governance strategies. Additionally, it provides valuable insights into the conservation, regeneration, and management of other similar heritage tourism destinations.

This research offers novel insights into the revitalization and tourism management of historic districts from the perspective of user behavior. The study findings enable planners and administrators to recognize tourists' behavior patterns accurately and evaluate the tourism attractiveness and potential challenges of each small public space unit. This understanding facilitates the development of precise spatial governance and tourism management strategies. For instance, strategies such as differentiated functional adjustments, spatial optimizations, and controls over tourist flows can be tailored to various types of public spaces, enhancing sustainable tourism development in historic districts.

This study acknowledges several limitations. First, the technical limitations of the Wi-Fi probes cause concerns about data accuracy and privacy risks [34]. Second, this study has not yet thoroughly examined the tourists' perceptions as well as the impact of the built environment. Third, this study has only provided empirical evidence from a single historic district and lacks comparative studies with other similar historic districts. Therefore, future research should explore the relationship among various built environment elements, tourists' perceptions, and tourist preference dynamics by combining other techniques. Comparative studies should also be conducted in several other historic districts, such as those along the Grand Canal.

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