

Article

RETRACTED: Spatiotemporal Analysis of Tourists and Residents in Shanghai Based on Location-Based Social Network's Data from Weibo

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Abstract: The aim of this study is to analyze and compare the patterns of behavior of tourists and residents from Location-Based Social Network (LBSN) data in Shanghai, China using various spatiotemporal analysis techniques at different venue categories. The paper presents the applications of location-based social network's data by exploring the patterns in check-ins over a period of six months. We acquired the geo-location information from one of the most famous Chinese microblogs called Sina-Weibo (Weibo). The extracted data is translated into the Geographical Information Systems (GIS) format, and compared with the help of temporal statistical analysis and kernel density estimation. The venue classification is done by using information regarding the nature of physical locations. The findings reveal that the spatial activities of tourists are more concentrated as compared to those of residents, particularly in downtown, while the residents also visited suburban areas and the temporal activities of tourists varied significantly while the residents' activities showed relatively stable behavior. These results can be applied in destination management, urban planning, and smart city development.

Keywords: LBSN; KDE; Weibo; tourism; GIS

1. Introduction

Mining patterns and gaining useful insights from spatiotemporal data has been an important research topic in recent years. Due to the abundant potential applications of Location-Based Social Networks (LBSN) nowadays, the resulting information has become much more valuable, especially from a practical point of view. Application areas like urban tourism are associated with reviving the urban texture and cultural development, as well as improving the local economy and urban vitality [1,2]. However, it may have several challenges, for example the stability of social interaction among tourists and residents [3]. The excessive number of tourist activities can also affect the attractiveness of various urban venues for both tourists and residents [4], which may result in exceeding the tolerance level of residents and cause several problems [5]. The residents of several cities reported the same notions by blaming tourists for annoyances such as dirt, noise, and crowded cafes, bars or public transportation [6]. Therefore, it is important to analyze the activities and behavior of tourists from time to time in order to cope with these kinds of problems and better plan for such situations.

The spatiotemporal analysis of tourists mainly involves their movement, interactions, as well as the types of activities they perform in urban spaces within the city, such as what venues are visited at what times [7,8]. Many studies have been conducted on this topic, but mostly focused on movement

patterns, spatial distribution, and analyzing the factors influencing the tourists' behavior (e.g., [9–11]). However, interactions between the tourists and residents can be better studied by combining and comparing the spatiotemporal patterns of both groups, which provides useful insights to better understand their behavior, improve attractions, transport, services, and marketing strategies of a city, based on the actual facts from users' data [12]. Apart from that, the understanding of the characteristics of various venues within a city may help in knowing the activity patterns of tourists and residents within the city [13].

The recent studies comparing spatiotemporal patterns are based on check-ins performed from relatively limited tourism venues [4,13–16], making it difficult to analyze the various activities performed by tourists and residents. Several problems related to crowd flow, conflicts, and congestion have been pinpointed by these studies. However, studying and comparing the activities of both tourists and residents at various kinds of venues may help in revealing several patterns in terms of tourism-related affairs in a city. Additionally, by exploring patterns for when and where tourists and residents have encountered at various venues, along with the nature of the venues, it can potentially change the competition for urban areas between both groups and improve avoidance behaviors and crowd management. Such types of analysis can be beneficial by indicating the patterns in the preferences of tourists and residents, and providing us with the potential insights that are crucial in achieving more sustainable cities, and for marketing, managing, and planning tourism activities and attractions.

The aims of the current study include—(1) temporal analysis of tourists and residents of Shanghai at different times (including daily, weekly and monthly periods, from 1st January to 30th June, 2017); (2) classification of venues with tourists' and residents' check-ins; and (3) analyze and compare spatial patterns to find the concentration of tourists and residents of Shanghai city, and identify which parts of Shanghai are affected by their activities. The research is carried out in one of the most developed cities of China, Shanghai. Shanghai can be considered as typical city within the context of urban tourism. It is difficult to find the exact related data about the tourist in China (e.g., [17]). However, several previous studies (e.g., [18,19]) used Weibo, which is one of the most popular microblogs and online networking platform in China, to analyze the tourists' behaviors. Therefore, the current study attempts to use check-in data from Weibo to differentiate tourists and residents in Shanghai and perform the spatiotemporal analysis for both groups in the city.

The rest of the paper is structured as follows; Section 2 covers the related work on LBSNs' data analysis through research on its significant applications in various fields, research articles related to Weibo, China and Shanghai, and tourists' and residents' spatiotemporal patterns. Section 3 includes an overview of the research design for the current study, including a detailed description of the methodologies for data collection and preparation, and temporal and spatial analysis. The results along with illustrations of our findings are presented in Section 4 and we conclude our study with a brief discussion of the limitations and possible future work in Section 5.

2. Related Work

An exponential increase in big data research has been seen in the last few decades, and research in the big data field has gained the tremendous attention of many researchers as compared to other fields of Computer Sciences. One of the most important and influential sources of big data is LBSN because of its popularity and widespread use all over the globe [20]. The users share their locations, interest, and activities on LBSNs, thereby generating huge amounts of data that provides the opportunity to conduct various kinds of research in different fields. The use of LBSN for analysis has been discussed by Lindqvist et al. [21], followed by many studies, like socio-spatial patterns, and empirical studies based on LBSNs' data [20,22,23]. For instance, the check-in data of 10,000 users from a famous LBSN called Foursquare was used by Preoțiu-Pietro & Cohn [20] for understanding user activity patterns in different categories. A dataset containing data from two different LBSNs, i.e. Foursquare and Gowalla, was used by J.-D. Zhang & Chow [24] to observe similar patterns and presented the personalized

geo-social recommendations. Activity patterns at 'Food' venues were studied by Alrumayyan et al. [25] in Riyadh, Saudi Arabia using Foursquare data to examine the popularity of different venues related to food. The check-in data of more than 19,000 Swarm (App of Foursquare) users from New York, San Francisco, and Hong Kong city was studied by Lin et al. [26] to analyze user preferences and associations among various venue categories at different times of the day. Loo et al. [27] used LBSN data and the kernel density method to study the spatial distribution of road crashes in Shanghai.

Most of the previous research has been carried out using data from LBSNs like Foursquare, Twitter etc., to find different patterns including human mobility, activity, urban planning, and venue classification etc. [28]. However, Weibo, one of most famous LBSNs in China, has been proved to be an efficient source of data for LBSN-based studies. A case study of Shanzen was conducted by Gu et al. [29] to analyze the check-ins for examining the attraction features of tourism venues using Weibo data for the time period of 2012 to 2014. Similar data were used by Long et al. [30] for human mobility and activity patterns, who proposed a framework for analyzing the growth of urban boundaries of Beijing. Shi et al. [28] also used Weibo data for examining tourism crowds in Shanghai by analyzing the check-ins in order to identify the popularity of tourism venues and the associations between these venues, with the help of sentiment analysis from user opinions. Ullah et al. [31] used Weibo data to analyze the spatiotemporal patterns in green spaces for urban studies. The check-in behavior, along with gender differences, based on data from Weibo from early 2016 was presented by Rizwan et al. [32,33].

In today's era, urban tourism takes place in a variety of venues throughout a city like theme parks, historic places, and museums, and also extends to shopping malls, local neighborhoods, and markets etc. [34]. Modern cities are multifunctional in nature and a variety of users, including tourists and residents are making use of different resources like transportation, accommodation, and restaurants; that are not exclusive for tourists [35]. In most cases, tourists and residents are not set apart and rather increasingly share the same venues and facilities within a city [36], which can be observed by analyzing and comparing the spatiotemporal patterns of both groups in the city. In order to better compare the spatiotemporal patterns, it is important to discuss the temporal and spatial patterns as well as the nature of the places where the tourists and residents may interact [37]. Gu et al. [29] identified resident and non-resident areas from the location of the registered user ID to find the origins of social media users. A study of users in eight European cities conducted by García-Palomares et al. [14] proved that there is a high concentration of tourist activities at tourist hotspots as compared to the residents' activities. Vu et al. [38] conducted a more specific analysis by identifying seven key areas of interest for tourists, mostly concentrated in the downtown area of Hong Kong. Paldino et al. [13] and Kotus et al. [4] also confirmed that tourists are more active in central areas of the city, whereas residents are active in socializing places like squares, parks, and sports facilities, by comparing both the tourists' and residents' data. In urban tourism, the activities of tourists and residents are not only unevenly distributed in space, but also in time [37,39]. Li et al. [40] presented the uneven distribution in days-, weeks-, and holidays-related differences of the Chinese tourist activities in Lijiang. Liu & Shi [41] suggested the same results by conducting a study of the city of Hangzhou. According to Liu et al. [42], the temporal activities of residents are regular at a collective level, but substantially different at an individual level due to the difference in schedule and routine. On the other hand the tourists spend more time in urban areas in which the tourism highlights (in terms of facilities and heritage) are concentrated, while the residents spend very less time based on their daily, weekly, and annual routine [8]. Ebrahimpour et al. [43] reviewed the main approaches to extract features in the behavior of users from crowd flow analysis. Fistola et al. 2019 [44] conducted similar studies for urban planning, focusing on the need of such tools and approaches to achieve urban smartness.

However, to the best of our knowledge, there is no comprehensive study for the area of Shanghai that combines and compares both the temporal and spatial characteristics in check-ins of tourists and residents, and extends the user activities to different venue classes within Shanghai city. Our goal is to study the volatility and compare the activities of tourists and residents at different time scales (e.g.,

time of day, day of week, six months; demonstrating the validity of Weibo data and temporal behavior) in association with the type of venues to find the spatial patterns in these activities for both groups using Kernel Density Estimation (KDE).

3. Research Design

3.1. Study Area

This study was conducted in Shanghai, one of the most famous and developed cities of China, situated on the eastern edge of Yangtze River Delta in-between $30^{\circ}40'$ - $31^{\circ}53'N$ and $120^{\circ}52'$ - $122^{\circ}12'E$ with a total area of 8,359 square-kilometers. It is a spatially dispersed, highly developed urban destination with lots of scattered historical and modern tourist attractions (including the famous Disneyland and other well-known tourism highlights). In 2016, Shanghai has been divided into 16 districts and one county; namely, Baoshan, Changning, Fengxian, Hongkou, Huangpu, Jiading, Jingan, Jinshan, Minhang, Pudong New Area, Putuo, Qingpu, Songjiang, Yangpu, Xuhui, and Chongming, respectively [45] as shown in Figure 1.

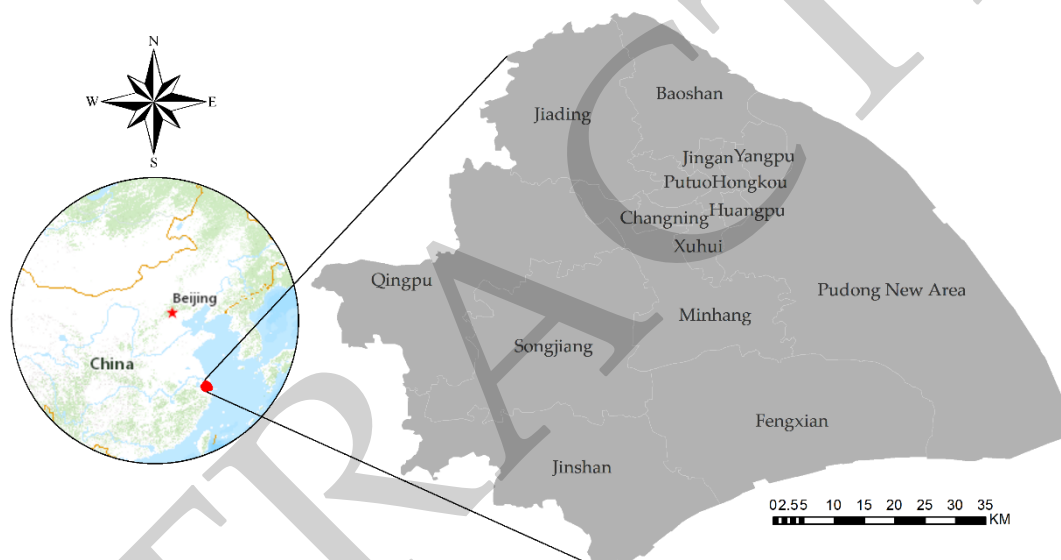


Figure 1. Study Area.

As the economic city of China, Shanghai connects China to the global economy. The total Gross Domestic Product (GDP) of Shanghai in 2016 was 2.7 trillion Chinese Yuan, with an average 7.4% increase over the past 5 years, and the per capita GDP reached up to 15,290 USD (103,100 Yuan). With an average population of 3,854 people per square kilometers in urban areas, Shanghai has become the first city in China and fifth in the world regarding its population with around 0.66 million people moving in annually. Its population reaching from 16.74 million to 23.02 million during the last decade from 2000 to 2010, increased by 37.53% with more than 24 million residents at the end of 2015 [46]. The main reason for this growth is the large number of migrants and tourists, which made up 39% of the total population of Shanghai in 2010. The recent master plan greatly emphasis on providing more facilities regarding development and administrations for the betterment of tourists and residents of Shanghai (Shanghai Master Plan (2016–2035) [47]. Shanghai is a world-famous tourist destination with many renowned attractions, such as Oriental Pearl, Lujiazui, Century Park, Yu Garden, Jing'an temple, Nanjing East Road, and the Bund [48] etc., mostly situated in the city center, while there are more than 800 parks in different parts of the city.

3.2. Data Acquisition and Preparation

The primary inspiration in the use of LBSN is to share interests and activities, and thereby build new and close social relationships, enabling researchers to discover patterns in users' activities and preferences from the big data generated by the LBSN. The data source for this research is Weibo, regarded as one of the biggest and most popular microblogs in China, which allows the users to 'check-in' from any location using their mobile devices [19]. According to Weibo Data Center [49], the total number of monthly active users in China reached 462 million by December 2018, which is about one third of its entire population. Weibo provides a python based public Application Programming Interface (API) to search and download the geo-tagged check-in records which can be used as a source of analysis for spatiotemporal patterns [18,50]. We used Weibo API to collect data in specific areas of China, specifically Shanghai city during 2017 and initially there were approximately 3.5 million check-ins of about 2 million users. The data acquired from Weibo was in the standard Java format, namely Java Script Object Notation (JSON), which was pre-processed for analysis.

The initial dataset included several attributes such as User_ID, Gender, Origin of Registration, Check-in Date/Time, account creation Date/Time, Location_ID, and text messages etc., The dataset was first filtered for anomalies, missing attributes, and attributes irrelevant to our study. In order to extend our study to different types of venues and to make it more significant by considering only the important destinations, we included venues having more than 100 check-ins within the study period of six months. We differentiated between the residents and tourists based on their origin of registration. The final dataset included 222,525 check-ins (102,750 tourists and 119,775 residents) at 722 different venues for the time period of six months (January to June 2017). The sample of the final dataset is shown in Table 1.

Table 1. Dataset sample.

User ID	Date	Time	Gender	Origin	Location ID	Latitude	Longitude	Location
18 ... 73	6/30/2017	22:06:16	m	Shanghai	B2 ... 93	121.323346	31.258411	HSBC_Court
58 ... 96	6/30/2017	11:11:58	f	Zhejiang	B2 ... 93	121.395081	31.31339561	Shanghai_University
31 ... 23	6/30/2017	18:00:59	m	Jiangsu	B2 ... 9B	121.58817	31.310072	Golf_Training
51 ... 16	6/30/2017	19:13:45	f	Sichuan	B2 ... 9B	121.345023	31.283799	Baili_Life_Plaza

3.3. Analysis Methods

We performed temporal analysis of the dataset to explore various daily, weekly, and monthly patterns in the activities of tourists and residents based on their check-in frequencies at different time intervals. Various check-in venue categories were examined to investigate where users used LBSNs more actively. The venue categorization was done by comparing the latitude/longitude and location names from the dataset with the nature of the actual locations all over the city that can be used for further analysis for extracting useful patterns in each category. This study includes famous and most frequently visited locations and therefore, highlights venue categories bearing the maximum number of check-ins by the tourists and residents. The overall framework of our research methodology is shown in Figure 2.

We used KDE for the spatial analysis to observe and compare the geo-data for tourists and residents on the map. We collected the map attributes from OpenStreetMap and used Shape files on ArcMap with a built-in Python programming platform for the density estimation within the study area of Shanghai and a gray background in order to highlight the density more clearly on the map. OpenStreetMap is the geo-information platform for providing real-time and user-generated contents related to the global map, including various attributes of maps like roads, canals, streets, and districts etc. which is available free of cost and is one of the most widely used by researchers to analyze and

visualize the geo-spatial data [51]. The KDE is a multivariate method that uses random sampling of data for estimating the density. We can calculate the density as shown in Equation (1):

$$f(l) = \frac{1}{nh} \sum_{i=1}^n K\left(\frac{l-L_i}{h}\right) \quad (1)$$

where $f(l)$ (i.e. KDE) is the weighted average of the points near l , h is the bandwidth (or search radius), the sample size is n , and K is the Gaussian function at $l - L_i/h$. The Gaussian Kernel Function $K()$, provides an efficient way of estimating the density [52]. The surface value is largest at the location of L_i and decreases with rising distances from that point, reaching zero at the search radius from the point. With the bandwidth setting principles, we used the default bandwidth (search radius) through ArcMap 10.6.1 to calculate the KDE results.

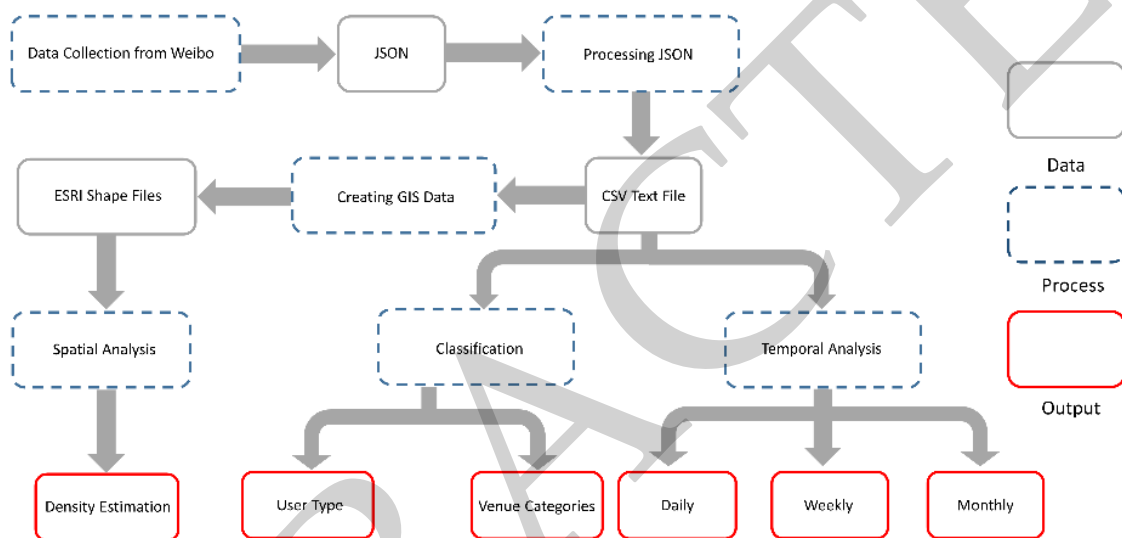


Figure 2. Framework.

4. Results and Discussion

With the advancements in online services, wireless communication, mobile devices, and location sharing technologies, LBSNs like Facebook, Foursquare, Tweeter, and Weibo etc., are attracting researchers' attention to utilize the huge amount of data generated by these LBSNs for their studies. It can be used to extract very useful information for tourism, urban planning, crisis and disaster managements, and for other fields of study involving big data with high spatiotemporal resolutions. This section includes the results and discussion of the current study.

4.1. User and Venue Distribution

The tourists and residents are classified based on their origin of registration from the Weibo dataset. The total number of check-ins in our dataset is 222,525, 102,750 of which (accounting for nearly half of the total number) are performed by tourists and 119,775 are from residents. The check-in distribution of tourists from different provinces of China and overseas countries is given as follows.

It can be observed in the above Figure 3 that most check-ins were made by tourists from Jiangsu Province, followed by Zhejiang, Beijing, and Anhui. The check-ins by the tourists from the eastern provinces (e.g., Jiangsu, Zhejiang, and Anhui) can be seen in huge figures, while tourists from the relatively underdeveloped western provinces such as Qinghai and Tibet had the least tourists' check-ins. One of the main reasons behind this [53] may be because of the strong family ties and close geographical proximity between the areas. The greater number of tourists from places such as Beijing and Zhejiang may be because of the tourism policies, particularly the Individual Visit Schemes [54].

Other reasons may include the internet adoption and distribution of Weibo users throughout the nation. The relatively higher number of active Weibo users in the eastern and central south China than the nation’s average [49] may be because of the uneven economic growth rate and the internet development level in these areas [55]. Apart from Chinese tourists, a significant number of the check-ins were recorded by the tourists from overseas countries (mostly from the United States, United Kingdom, Japan, Australia, France, Canada, Singapore, and Korea etc.) may be because Shanghai is considered as one of the most developed cities as well as the economic hub of China.

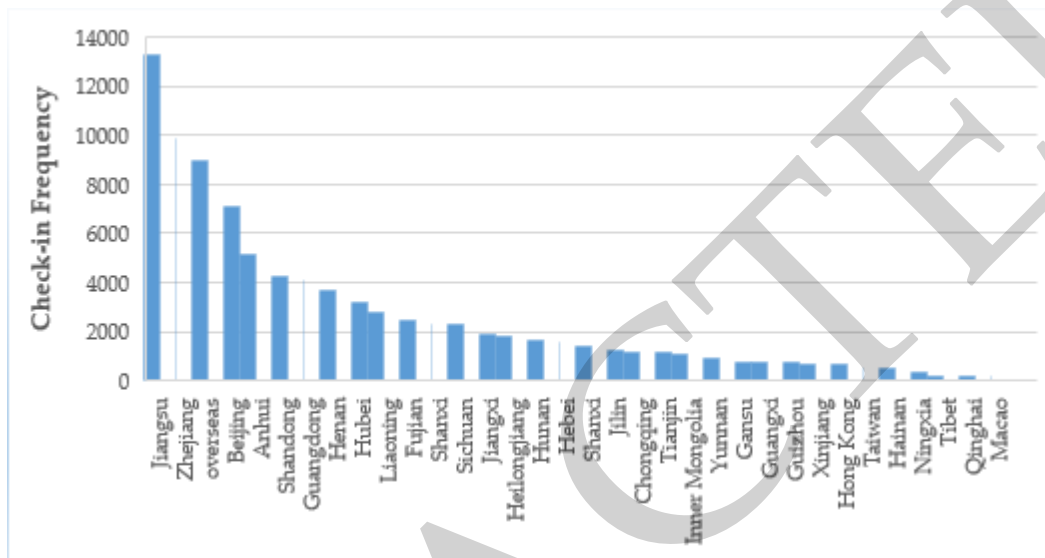
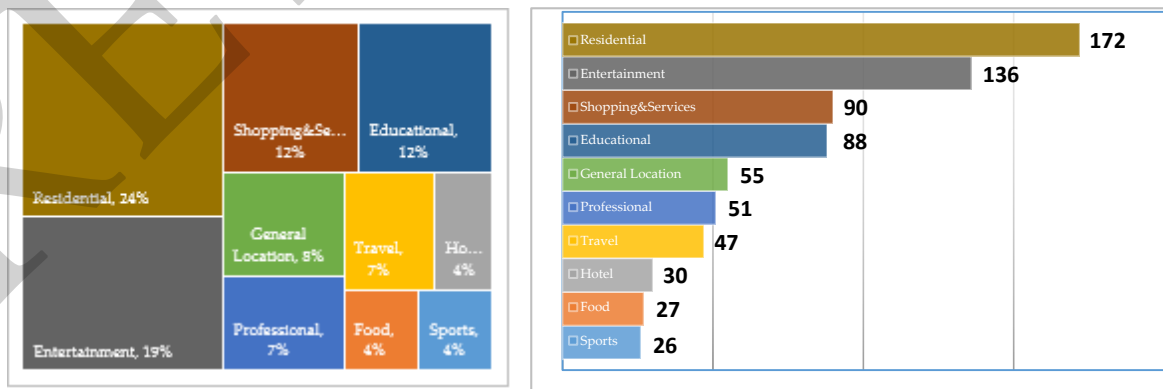


Figure 3. Frequencies of tourists' check-in from different provinces.

An advantage of using data from LBSNs is the ability to identify the venue of check-in activity. Each check-in records the latitude and longitude of the actual location by the LBSN (such as Weibo) [56]. When searched in the data, this latitude/longitude gives the exact location on a geo-map. This location can be used to gather information about the nature of the visited venue. We classify the venues in our dataset based on their nature and activities performed at these venues. We use the most general type of the hierarchy, containing 10 different venue types—‘Educational’, ‘Entertainment’, ‘Food’, ‘General Location’, ‘Hotel’, ‘Professional’, ‘Residential’, ‘Shopping&Services’, ‘Sports’, and ‘Travel’, based on the most frequent checked-ins’ latitude/longitude and real-world locations in Shanghai as shown in Figure 4.



(a)

(b)

Figure 4. (a) Distribution of Locations in Categories. (b) Number of Locations in Each Category.

We explore various usage patterns by applying the same category distribution to the whole data in our dataset through different characteristics of the prescribed categories along with the tourists and residents as shown in the Table 2.

Table 2. Venue types visited by tourists and residents.

Venue Category	Total No. of Check-Ins	Total No. of Users	Check-Ins by Tourists	Check-Ins by Residents
Educational	28139	20535	10479	17660
Entertainment	55747	42393	29993	25754
Food	8015	4930	2939	5076
General Location	13618	10973	7435	6183
Hotel	10028	6935	5731	4297
Professional	11517	8270	4642	6875
Residential	28928	23508	12479	16449
Shopping&Services	33923	26280	13757	20166
Sports	14771	11256	6989	7782
Travel	17839	11818	8306	9533

To further compare the activities of the tourists and residents, we provide the distribution of both the groups in different categories in Figure 5.

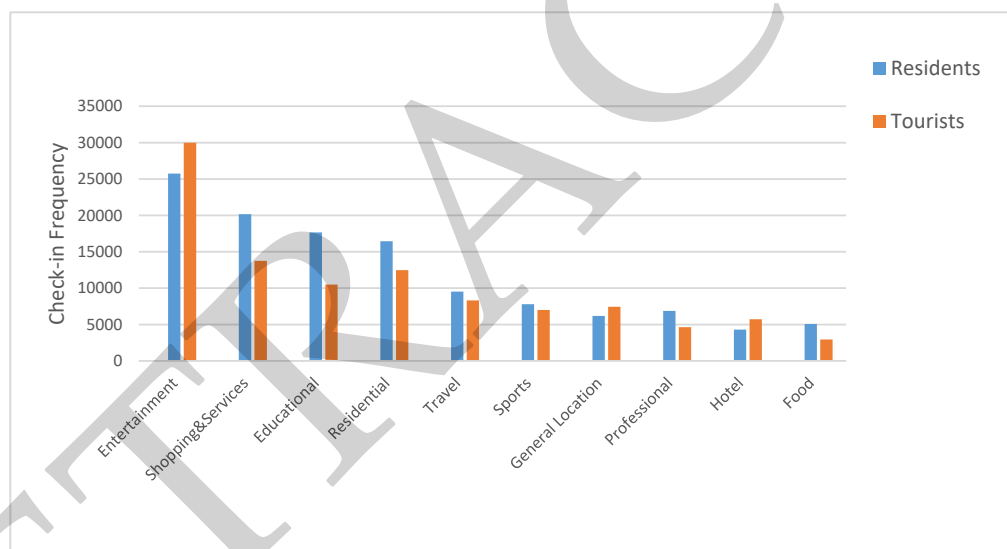


Figure 5. Distribution of tourists and residents into venue categories.

Figure 5 illustrates that most of the check-ins were made from entertainment places like theme parks, and historical sites etc. by both the tourists and residents, followed by shopping & services conforming the typical behavior of users to share their visiting and happy moments with the social networks, especially for the tourists as entertainment is the core activity of tourism while shopping is one of the regular activities performed by residents. The check-ins from educational, residential, travel, sports, and food venues by residents are significantly higher than tourists while at hotels, general locations, and obviously entertainment venues show a greater number of tourists as compared to the residents. This behavior shows the validity of the dataset, corroborates with the previous studies, and also highlights the type the areas where the tourists and residents may interact with each other.

4.2. Temporal Patterns

In order to gain knowledge about the temporal patterns and compare the behavior of the tourists and residents of Shanghai, we analyzed the check-in frequencies of both groups with respect to time in daily, weekly, and six-month periods as shown below.

Looking at the daily distribution of tourists' and residents' check-ins uncovers significant temporal patterns as presented in Figure 6a. The average frequencies show that the residents' activities start early in the morning as compared to the tourists, but the tourists' activities comparatively continue till late night. Another fact is that the residents have relatively gradual and higher check-ins throughout the day, but the tourists are more active later in the day, exceeding the residents' check-ins at about 11 AM. Figure 6b demonstrates a similar behavior for both tourists and residents, and the common patterns in their activities i.e. check-ins start rising on Fridays and are highest on the weekend, and less during the rest of the week. On the weekends, however, there is a significant difference between the check-ins of tourists and residents as the residents are comparatively more active on Saturdays but the tourists show more activities on Sundays. The general higher number of check-ins on weekends may be because of the fact that leisure activities and tourism merit more memorizing and sharing than the routines and daily activities [41]. A clear comparison can be observed in Figure 6c showing various interesting patterns like peaks in the check-in frequency of tourists in early January followed by an immediate drop at the end of the month, which may be because of the different kinds of festivities related to the Chinese Spring Festival. On the other hand, there are unusual spikes in April in the activities of the residents of Shanghai, which could be because it is the best time of the year in terms of weather (Spring), festivals (April cherry festival), and holidays (Qing Ming Jie holidays) but most importantly, because two of the most famous and major events were held in April 2017, including the Formula 1 World Championship and the Shanghai Film festival [28]. In light of the previous studies, we exhibited that the temporal pattern of residents' activities varies less (but tremendously affected by mega events) than that of the activities of tourists in Shanghai, which are much more variable and often less stable over time by considering the day, week, and six-months as time intervals.

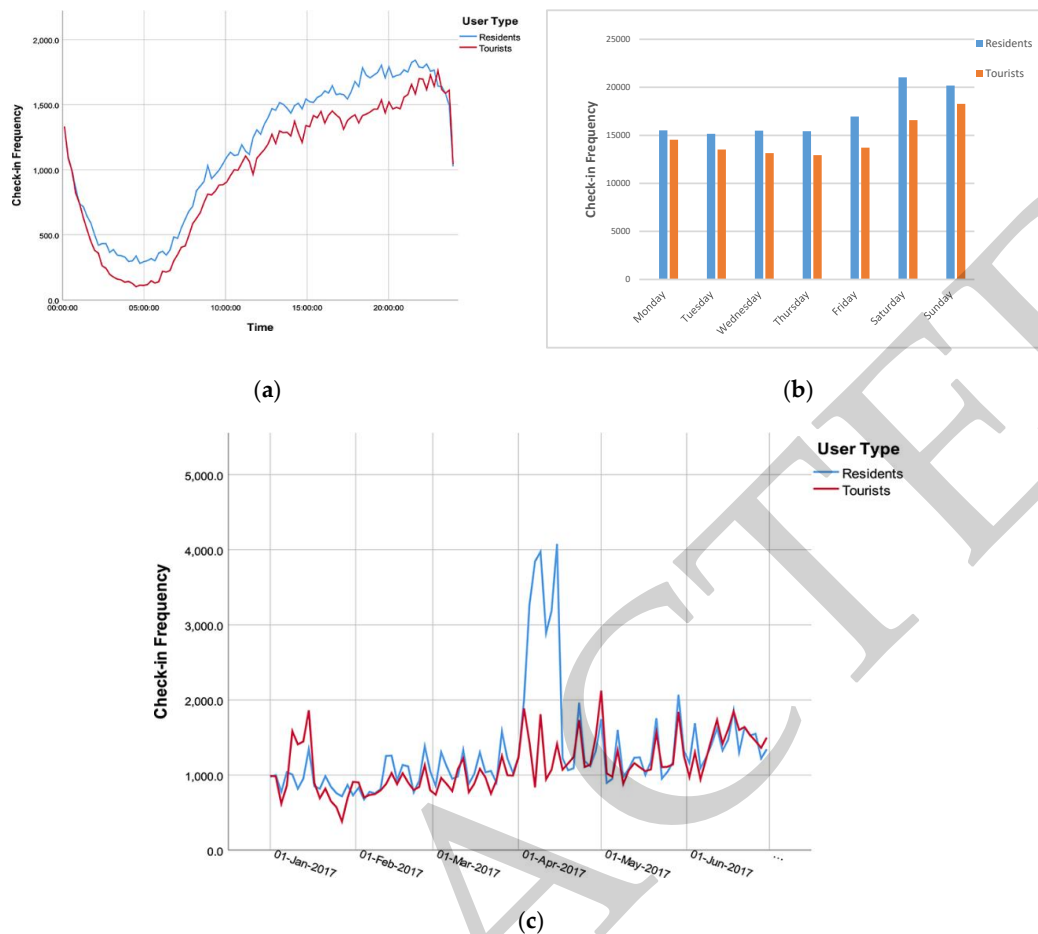


Figure 6. (a) Daily check-in frequencies. (b) Weekly check-in frequencies. (c) Check-in frequencies of tourists and residents for six months.

4.3. Spatial Patterns

In this section, we investigate the spatial analysis using density estimation of the total check-ins, and compare the activities of tourists and residents by using the geo-location data from Weibo on the map of Shanghai. For this purpose, we used map, including its features from OpenStreetMap because it contains the most recent updates of the map features [57]. The density estimation of overall check-ins of all the users in the dataset is presented in Figure 7.

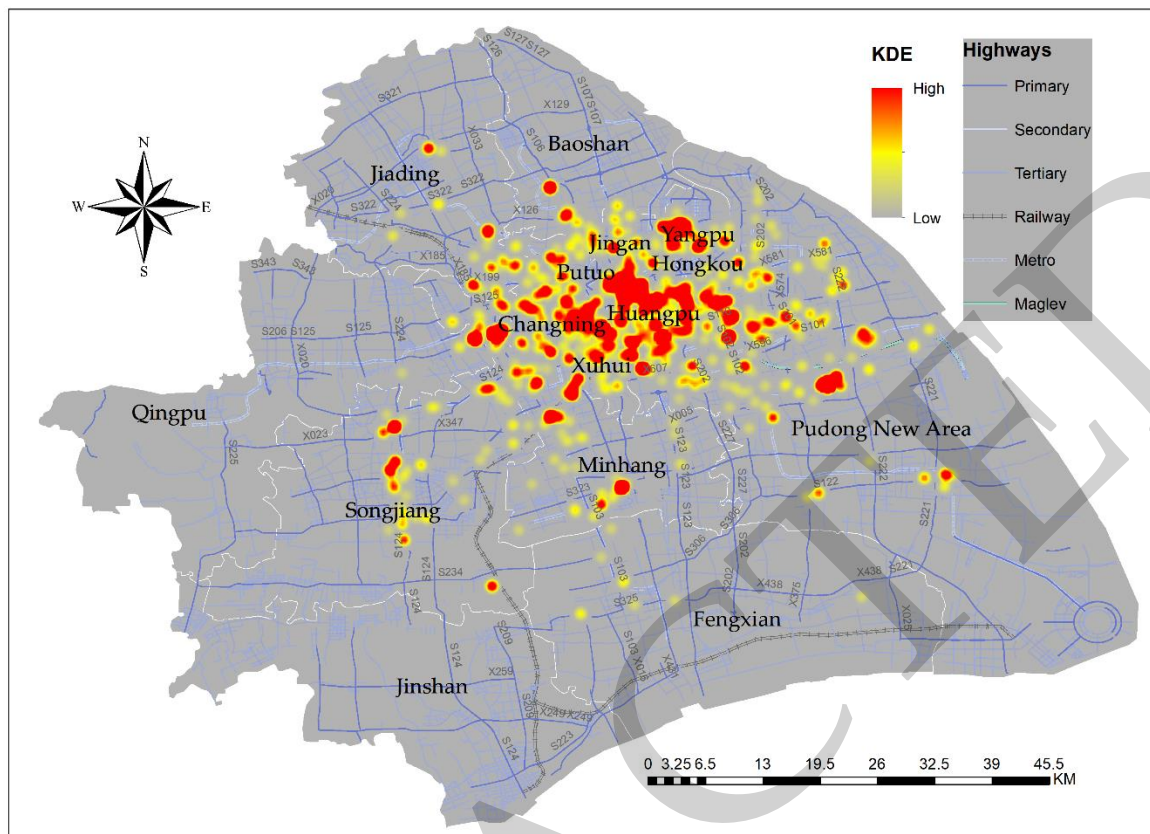


Figure 7. Kernel density estimation of overall check-ins in Shanghai.

The districts of Chongming, Hongkou, Huangpu, Jingan, Xuhui, and Yangpu; collectively called the downtown (or city center) of Shanghai, show higher concentrations of check-ins along with some parts of Baoshan, Jiading, Songjiang, Minhang, and Pudong New Area. As any modern urban city in the world, the downtown area of Shanghai has lots of landmarks, shopping malls, and office buildings, and many streets lined with restaurants, hotels, universities, temples, and markets (i.e. The Bund, Peoples Square, Nanjing Road, Shanghai Disney Resort etc.) which may be why it attracts a large number of visitors. These areas satisfy many people's interests, so visitors spend most of their time and activities in these areas. The airports in Pudong New Area and the railway station in Minhang also have hotspots away from the downtown because these are the international and national transit hubs [58]. Similarly, the National Forest park and Shanghai Film park in the Songjiang district have high Heatmaps, besides that the Nanxiang Ancient Town also shows a Heatmap of high density away from the city center of Shanghai. The suburban areas are low-density areas of Shanghai with minimum check-ins performed by the users. The Heatmaps we found in Shanghai for Weibo users are similar to those previously mentioned by Rizwan et al. [59], who studied check-in data from Weibo for gender differences.

To highlight the difference between the activities of tourists and residents in various areas of Shanghai, the densities for both groups are calculated and presented separately in Figure 8. This way it is easy to spot the areas of Shanghai city with more and less concentrated activities by tourists as well as residents.

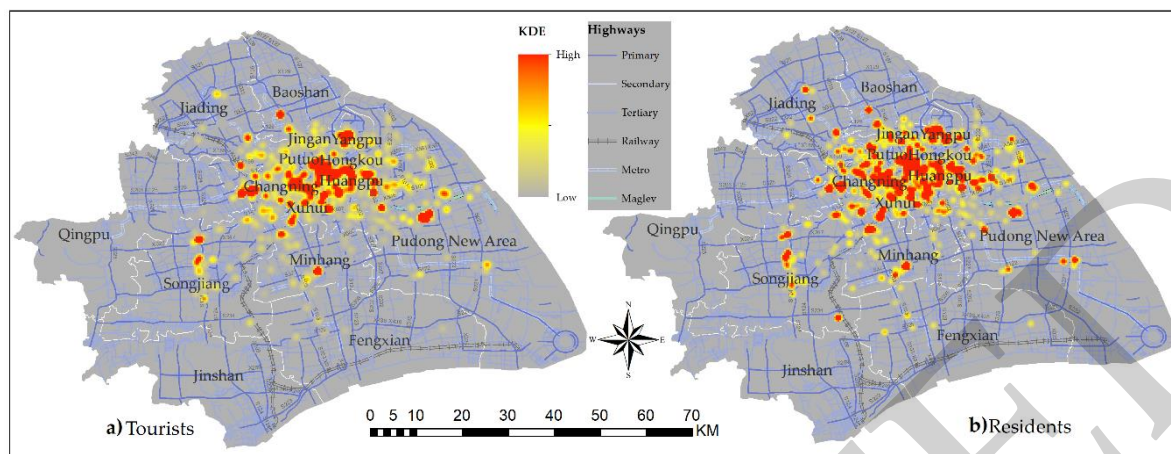


Figure 8. Kernel density estimation Heatmaps for tourists' and residents' check-in activity in Shanghai.

Figure 8 illustrates the spatial distribution and clearly shows the difference between the tourists' and residents' behaviors, representing their activities in Shanghai. It can be observed that the tourists' activities are much denser than those of residents. The tourists were highly active in the downtown areas, airports, and railway stations, and to a much smaller extent in various areas in the Jiading, Songjiang, and Pudong New Areas, while the residents were active in the same areas but also show a high concentration with a larger radius. The figure also reveals that the downtown area is the most popular among both tourists and residents, while residents also like visiting more diverse places like natural parks, and Nanxiang Ancient Town etc. The reason for this may be because most tourist attractions, popular restaurants, shopping, and nightclub facilities are concerted in the downtown area. However, the spatial activities of tourists were more concentrated than the activities of residents, which is consistent with previous research studies [14,15]. Specifically, it can be observed that the tourists were concentrated in central downtown areas while the residents also visited suburban areas. The comparison between the densities of tourists and residents discloses a great deal of overlap between their areas of interest in Shanghai, which provides many chances for interactions between them.

5. Conclusions

In this article, we analyzed and compared the spatiotemporal patterns in the activities of tourists and residents at different venues in Shanghai over a period of six months. We contributed to the current LBSN and tourism literature by; a) comparing the activity patterns of tourists and residents in one study, while most previous studies focused on tourist activities alone (e.g., [9,11]); b) classifying and extending the analysis to different venue classes, while most studies considered only specific tourism areas (e.g., [14,29]); and c) exploring the spatiotemporal patterns in activities for both tourists and residents, while most studies consider the movement of tourists in a city (e.g., [28,60]).

The results revealed that the activities of tourists in Shanghai are more spatially concentrated, especially in the downtown areas, while the spatial patterns in the activities of the residents of Shanghai were more dispersed, extending to suburban areas. The temporal results revealed that the activities of the tourists vary significantly during the day and between weeks and months. However, the temporal patterns in the activities of residents are relatively stable. From the visiting location perspective, the frequency of tourists' check-ins exceeds the residents at entertainments, shopping, hotels, and general locations. Famous tourist attractions in the downtown area of Shanghai, such as The Bund and Shanghai Disney Resort, revealed high concentrations in activities by tourists. Other urban attraction areas such as Nanxiang Ancient Town, and National Forest Park etc., away from the downtown were preferred by residents. Therefore, most encounters between residents and tourists are likely to happen in these areas. These results are important and can be used by the tourism industries to improve management and marketing. The information regarding the areas attracting most tourists may help

to develop and fine-tune marketing strategies, facilities, and services. The research also provides insights about possible overcrowding at specific areas. These results can also support policy making and planning to endorse more sustainable tourism in the city.

The research is carried out using Weibo check-in records that proved exceedingly useful for spatiotemporal analysis in Shanghai because the time-stamped and geo-tagged data of Weibo provide detailed attributes to differentiate venue types, tourists, and residents. However, the check-in data from Weibo also presented some limitations in our analysis, such as not all tourists may make use of Weibo when visiting Shanghai and residents also may use locations-based social network platforms other than Weibo which implies that the results could represent subsets of tourists and residents in Shanghai. Therefore, the reliability and quality of Weibo data for spatiotemporal can be improved by cross-referencing its results with other studies and data sources. In the future, we will try to focus on analyzing various motivations, characteristics, perceptions, and attitudes, using more advanced techniques like machine learning and sentiment analysis, of tourists in Shanghai, as they are increasingly significant users of the city.

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