Chapter 10
Revealing the Spatial Preferences Embedded in Online Activities: A Case Study of Chengdu, China

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Abstract Online activities based on various social media applications are gradually becoming a vital social activity issue in the mobile Internet era. This study aims to reveal the spatial preferences embedded in this new type of urban life to better plan and design future cities. With two different types of social media data—online location tagging from Weibo and online reviews of POIs on Dianping—we conducted a quantitative analysis to explore the relationship between online activities and the built environment elements. The results suggested that online activities remain associated with urban entities, and the activity represented by Dianping reviews revealed more significant spatial preferences than that described by Weibo check-ins. The results also showed similarities and differences between spatial choices of those who engage in these two activities. These findings allow for an in-depth understanding of contemporary cities' complexity and provide new opportunities for integrating cyberspace and city space.

Keywords Online activity · Social media data · Built environment · Spatial preference · Urban design

10.1 Introduction

Information and communication technologies (ICTs) and Internet-based applications have been developing rapidly in recent years. According to Internet World Stats,[1] as of 30 June 2020, the internet penetration rate had risen to 62%, while in China, this number reached 67.0%. Facilitated by the Internet's convenience, people's social

[1] Internet World Stats is an international website that features up-to-date data on world internet users, population statistics, social media statistics, and internet market research data for over 246 individual countries and world regions.

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and work habits are changing (Kellerman 2020). In this context, people can engage in activities that once required a fixed location and connection with greater flexibility (Ratti and Claudel 2016). The global digital network of the Internet has been reconstituting the relationships between people and information (Mitchell 2000), impacted how and where we locate ourselves, affected how we utilize the traditional functions of cities (Batty 2018), and will eventually change the interactions between urban space and activities (Kellerman 2020). Online activities are the most notable activities nourished by the Internet and cover politics, activism, consumption, and sharing, and they, to some extent, are combined and correlate with offline activities (Hirzalla and Zoonen 2011). As a result, online activities' potential to stimulate urban creativity and public participation from the perspective of urban development has also been emphasized (Ratti and Townsend 2011; Salvia and Morello 2020). Besides, a growing number of scholars have begun to advocate for the integration of online activities and urban space (Lorente-Riverola and Ruiz-Sanchez 2018; Sadowski 2020). To better realize the vision of the future integration of cyberspace and urban space, it is necessary to deeply understand these online activities and their relationship with the urban space in which our daily lives are contained.

Fortunately, the development of ICTs has not only reshaped urban life but also provided an alternative to the lengthy and costly collection of survey data (Sulis et al. 2018), bringing unprecedented opportunities for depicting urban activities and identifying their associated spatial factors (Qin et al. 2019; Sung et al. 2015). Online activities, especially those on social media networks, attract much attention, as they provide a new context for studying human activities (King et al. 2014; Shaw et al. 2016). These activities connect virtual communities with the real world and present a delicate balance between online activities and urban space (Liu et al. 2015). However, although an increasing number of scholars have used social media data to study urban vitality or explore the relationship between urban activities and space, most only used such data as a replacement for traditional survey data (Long and Huang 2019; Qin et al. 2019; Ye et al. 2018), failing to reveal this new urban phenomenon from the perspective of new activities and traditional urban spaces. In contrast, there have been a growing number of studies on online activities in other fields, such as sociology (Huang et al. 2016; Jiang et al. 2019), economics (Fogel and Zachariah 2017; King et al. 2014), and psychology (Meenar et al. 2019; Eshet 2012). Consequently, the relationship between these ubiquitous online activities and the urban environment remains unclear.

Do online activities occur in specific urban spaces? Do preferences vary significantly between different types of online activities? Although some studies have visualized the spatial distribution of certain types of online activities, such as geotagged tweets (Sulis et al. 2018), from a macro perspective, there is insufficient research on a more refined scale within the city. To address these questions, we used two types of online activity data derived from social media networks as our dependent variables because they can reflect the popularity of urban amenities and more accurately capture the "real" sense of function in people's minds (Shen and Karimi 2018;

Berger 2014). We also used some built environment elements as independent variables to explore the relationship between online activities and the built environment and compare the differences.

10.2 Methodology

10.2.1 Research Design

We studied the case of Chengdu, which is located in Western China and is the capital of Sichuan Province. As the earliest Internet celebrity city in China, Chengdu benefits greatly from various sources of online information and activities. Thus, a study of online activities in Chengdu can provide a reference for other cities. Street blocks were used for the analytical units, defined as individual polygons comprising street kerb lines. We generated these street blocks by dividing the area of streets/roads according to the approach proposed by Liu and Long (2016). Each of these blocks forms a ring or cycle of a minimum size. As a result, we obtained a total of 2,341 street blocks with an average area of 12,161.45 m^2 in the study area, the central city of Chengdu (Fig. 10.1). Street blocks were chosen as the analytical unit for two main reasons. First, street blocks delimited by street segments are regarded as natural boundaries for activities because roads are often considered barriers to functions or continuous activities (Jacobs 1961). Second, street blocks play an essential role in urban planning control and design guidance, especially in China, which may allow for the conclusions derived from this study to be easily converted into suggestions to assist planning and design practices.

To better reveal the relationship between online activities and the built environment, we selected two types of social media data to capture online activity. The first is online check-in data from Sina Weibo (the Chinese version of Twitter combined with

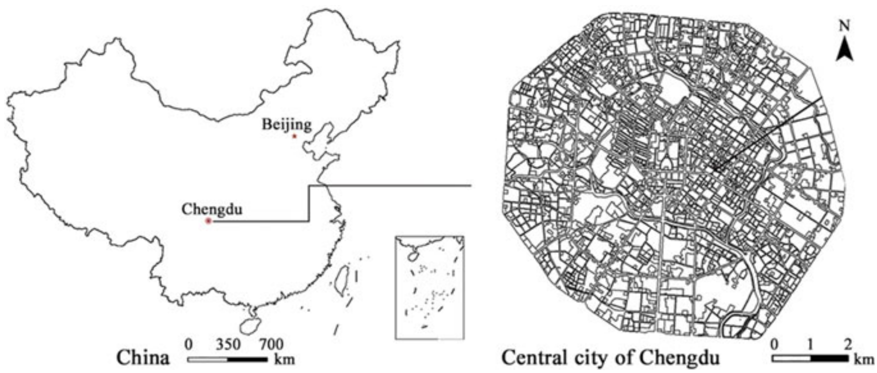

Fig. 10.1 Street blocks within the study area

Foursquare), the leading online microblogging platform in China, allowing users to publish, share and discuss short postings on their profile (Long and Huang 2019). Online check-ins show locations where users tag themselves on the online platform, reflecting users' willingness to share their location. The other type of data is online reviews from Dazhong Dianping (an aggregated social media tool for users to rate and comment on restaurants and other service industry companies in China) (Qin et al. 2019), which reveals people's ratings and preferences for different spaces. For the built environment, we applied the five Ds (density, diversity, design, destination accessibility, and distance to transit) introduced by Ewing and Cervero (2010) to better classify the built environment indicators and describe the location and spatial characteristics of each study unit. Then, we used ordinary least squares (OLS) to explore the correlation between online activities and the built environment. Before conducting a typical multiple regression analysis, we conducted a preliminary test to establish a basic understanding of the variables involved in this analysis. Finally, to verify the results' reliability, a robustness test based on the random forest (RF) method was applied to avoid bias in data sampling (Lin and Jeon 2006).

10.2.2 Variables and Data

Dependent variable

The dependent variables are the online activities represented by Weibo check-ins and Dianping reviews, which can be described as new online social activities (Table 10.1). For the Weibo check-ins, we scraped the check-in addresses shared on its official website (http://www.weibo.com) through its open API (application program interface), removed data from any providers whose addresses remained unidentified, and ultimately obtained 269,477 data points. For the Dianping reviews, we obtained available information on 99,763 service providers from its website (http://www.dianping.com), covering a similar period for the check-ins and including the name, detailed location data (longitude and latitude), and the number of reviews. We separately calculated the density of Weibo check-ins (Den_Check-in) and Dianping reviews (Den_Review) on each street block to represent online activities and study the spatial preferences they reveal.

Independent variables

Online activities represented by those generated from social media networks are usually accompanied by multiple offline activities (Hirzalla and Zoonen 2011) that might present similar spatial preferences as fully offline activities. Therefore, we selected independent variables from those commonly used in urban activity studies. In this study, we applied the five Ds to classify better and depict the urban spaces' location and characteristics (Table 10.1). They are common measures of the built environment and can capture features to moderate travel demand (Ewing and Cervero 2010) and promote functional connectivity (Shen and Karimi

Table 10.1 Descriptions of all variables (N = 2,341)

Variable	Main category	Indicator	Description	Mean	Std. dev
Dependent variables	Online activities	Den_Check-in	Weibo check-in density for each street block (#/km^2)	132,692.95	587,567.04
		Den_Review	Dianping review density for each street block (#/km^2)	9741.13	40,606.20
Independent variables	Density	Den_Catering	Density of each type of POI for each street block (#/km^2)	2920.75	6748.15
		Den_Retail		3584.34	7479.69
		Den_Education		585.73	1724.74
		Den_Finance		367.70	1321.67
		Den_SportFacility		287.94	1066.77
		Den_Transport		2381.64	11,213.47
		Den_Service		913.75	1853.68
		Den_Office		2316.74	5054.86
	Diversity	Mix_POI	Normalized degree of POI mixing, calculated by the formula Mix_POI = -sum(pi*ln pi), (i = 1,2,…, n) where n represents the number of POI types in a block and pi represents the standardized proportion of a specific POI type in a block	1.54	0.52

(continued)

Table 10.1 (continued)

Variable	Main category	Indicator	Description	Mean	Std. dev
	Design	Den_Junction	Density of surrounding road intersections for each street block (#/km^2)	524.96	1736.46
		BtA800	Street network configuration at the local scale (800 m) and global scale (15,000 m)	775.34	636.66
		BtA15000		3,059,149.71	6,696,977.65
	Destination accessibility	Dis_CityCentre	The Euclidean distances from each street block midpoint to the city centre and closest mall, tourist attraction, and place of recreation (m)	2782.18	1119.31
		Dis_TouristAttraction		503.20	397.67
		Dis_Recreation		113.81	114.41
	Distance to transit	Dis_Metro	The network distances from each street block midpoint to the closest subway or bus station (m)	371.97	214.83
		Dis_Bus		42.02	63.53
	Control variable	Den_Pop	The density of the population (of phone users) on each street block (#/km^2)	13,831,991.95	30,470,182.24

2018). Although they have appeared in other studies under different names or terms, they all reflect urban researchers' concerns about the density, diversity, and accessibility of built environments (Sung et al. 2015; Grant 2002). 1. Density is usually measured as the variable of interest in each study unit. The study unit in this research is the street block. The variables of interest are the densities of specific points of interest (POIs) in the street block, namely, catering services (Den_Catering), retail shops (Den_Retail), education services (Den_Education), financial services (Den_Finance), sports facilities (Den_SportFacility), transport facilities (Den_Transport), public services (Den_Service) and offices (Den_Office). Density was considered in this study because it provides information about how people use urban places and their attractiveness. 2. Diversity, as an important support for the creation of an active urban environment (Jacobs 1961; Grant 2002; Long and Huang 2019), measures the number of different uses or functions in a given area. Entropy is a widely used method (Ewing and Cervero 2010), whose low values indicate single-use environments and higher values indicate greater variety in land uses. This study used POI data to describe fine-scale functions and calculated their mixture (Mix_POI) to measure each street block's diversity (Shen and Karimi 2016). 3. Design includes the characteristics of the street network within an area. Small blocks or streets have been verified to be associated with urban activities (Sung et al. 2015; Long and Huang 2019). Therefore, we calculated the number of surrounding road intersections per square kilometre (Den_Junction) to describe the blocks' size. Besides, we introduced two indicators from the space syntax literature—the street network configuration at the local scale (800 m) and the global scale (15,000 m): BtA800 and BtA15000—to measure the design of streets and present their connectivity on a larger scale. 4. Destination accessibility measures the access to potential destinations such as the city centre (Dis_CityCenter), tourist attractions (Dis_TouristAttraction), and places for recreation (Dis_Recreation). Since the number of such sites is smaller than that of daily activity sites, we calculated the distance to the nearest point rather than their density. 5. According to Ewing and Cervero (2010), distance to transit is usually measured as the average of the shortest street route from an area to the nearest rail station or bus stop. This study calculated the network distance to the closest subway (Dis_Metro) and bus station (Dis_Bus). Destination accessibility and distance to transit elements are also regarded as essential to stimulating the interaction between various activities, considering their association with cost savings or efficiency maximization (Penn and Turner 2004). Besides, to better reveal preferences for online activities, we controlled for population density as a confounding influence in this study, measured as mobile phone user density (Den_Pop) (Table 10.1).

Based on the above indicators, we collected road network data and parcel data from the Chengdu Urban Planning Institute. We purchased data resources from one of China's largest communication operators for the anonymous grid-level population data. All the data were measured quantitatively using street blocks as the analytical units. Specifically, the values of the density and diversity indicators and the control variables were computed directly. The street network configuration was computed with the distance decay model[2] (Ye et al. 2017). We used the average values to convert the configurational values from the central street lines to street blocks. The values for the destination accessibility and distance to transit indicators used the geometrical centre of each street block as the starting point and the potential destination as the endpoint to calculate the Euclidean or network distance.

10.3 Regression Analysis

10.3.1 Preliminary Test for Regression

(1) **Data processing and transformation of variables.**

Because OLS regression requires the involved variables to be normally distributed, we examined the original data distributions of the dependent and independent variables. We found that most variables except Mix_POI, BtA800, BtA15000, Dis_CityCentre, and Dis_Metro have long tails. To achieve a normal distribution, we logarithmically transformed (Long and Huang 2019) these long-tailed variables. We examined the data distribution after the logarithmic transformation to ensure that all 20 variables were normally distributed.

(2) **Preliminary tests for independent variables.**
Before conducting the regression analysis, we employed Pearson's correlation analysis to examine the model's multicollinearity. Generally, if two variables have a Pearson's correlation above 0.8, there is a high degree of multicollinearity. The results showed that the correlation coefficients among all the variables were less than 0.8 (Fig. 10.2), which means that the multicollinearity was not very severe, and the model was relatively reliable.

10.3.2 Regression Results

We used OLS to estimate the model to understand the association between various built environment variables and online activities.

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[2] $\boxed{B_b = \sum_{i=1}^{n} BtAR_{(x)i} \frac{L_i/D_i^x}{\sum_{i=1}^{\alpha} L_i/D_i^x}}$; B_b = the configuration value of each block, $BtAR_{(x)\,I}$ = the configuration values of the surrounding streets, L_i = the lengths of the central street lines affecting the block, D_i = the shortest Euclidian distance from the central street lines to the block edges, $\boxed{\alpha}$ = the distance decay value.

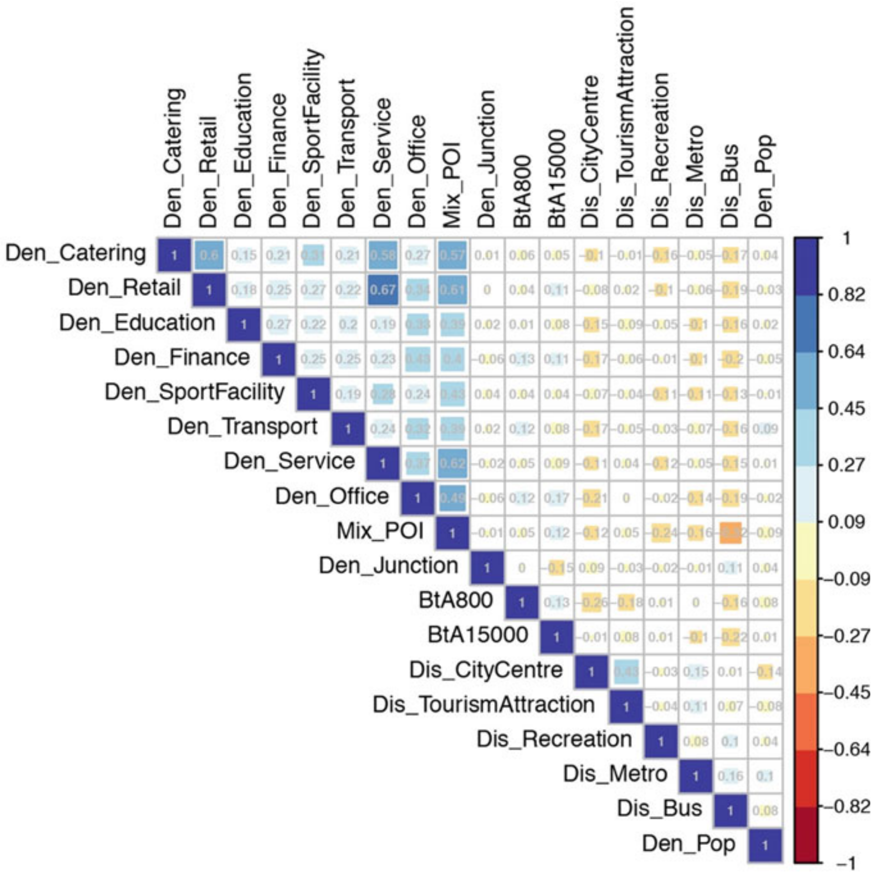

Fig. 10.2 Correlation examinations of all 20 independent variables

$$
\begin{aligned}
&\ln(\text{Den\_Check} - \text{in}) \text{ or } \ln(\text{Den\_Review}) = \beta_0 + \beta_1 \times \ln(\text{Den\_Catering}) \\
&\quad + \beta_2 \times \ln(\text{Den\_Retail}) + \beta_3 \times \ln(\text{Den\_Education}) \\
&\quad + \beta_4 \times \ln(\text{Den\_Finance}) + \beta_5 \times \ln(\text{Den\_SportFacility}) + \beta_6 \times \ln(\text{Den\_Transport}) \\
&\quad + \beta_7 \times \ln(\text{Den\_Service}) + \beta_8 \times \ln(\text{Den\_Office}) + \beta_9 \times \text{Mix\_POI} \\
&\quad + \beta_{10} \times \ln(\text{Den\_Junction}) + \beta_{11} \times \text{BtA800} + \beta_{12} \times \text{BtA15000} + \beta_{13} \times \text{Dis\_CityCentre} \\
&\quad + \beta_{14} \times \ln(\text{Dis\_TouristAttraction}) + \beta_{15} \times \text{Dis\_Recreation} + \beta_{16} \times \text{Dis\_Metro} \\
&\quad + \beta_{17} \times \ln(\text{Dis\_Bus}) + \beta_{18} \times \ln(\text{Den\_Pop})
\end{aligned}
$$

The analysis results are reported in Table 10.2. Since the VIF values for all the variables in each model were less than 5, no independent variables needed to be removed due to multicollinearity. Comparing the two models, the higher R2 of Model 2 suggested that online reviews were more dependent on the built environment, which could be explained by the fact that online reviews can only be recorded in places with POIs and are more closely linked to in-person offline activities than online check-ins.

Table 10.2 OLS regression results for each explanatory variable (N = 2,341)

Main category	Indicators	Model 1 ln(Den_Check-in)				Model 2 ln(Den_Review)			
		Beta	Std. error	Sig	VIF	Beta	Std. error	Sig	VIF
Density	(Intercept)	0.0000	0.0185			0.0000	0.0149		
	ln(Den_Catering)	0.0729	0.0254	**	1.8836	0.2815	0.0204	***	1.8836
	ln(Den_Retail)	0.0288	0.0276		2.2267	0.2976	0.0222	***	2.2267
	ln(Den_Education)	0.0790	0.0209	***	1.2796	0.0350	0.0169	*	1.2796
	ln(Den_Finance)	0.1007	0.0216	***	1.3693	0.0369	0.0174	*	1.3693
	ln(Den_SportFacility)	0.0937	0.0207	***	1.2609	0.0684	0.0167	***	1.2609
	ln(Den_Transport)	0.0753	0.0208	***	1.2631	0.1157	0.0167	***	1.2631
	ln(Den_Service)	0.1082	0.0278	***	2.2617	0.2402	0.0224	***	2.2617
	ln(Den_Office)	0.0246	0.0232		1.5777	0.0257	0.0187		1.5777
Diversity	Mix_POI	−0.0561	0.0325		3.0856	−0.2323	0.0262	***	3.0856
Design	ln(Den_Junction)	0.0129	0.0190		1.0625	−0.0418	0.0154	**	1.0625
	BtA800	0.0441	0.0198	*	1.1504	0.0499	0.0160	**	1.1504
	BtA15000	0.0068	0.0196		1.1229	0.0168	0.0158		1.1229
Destination accessibility	Dis_CityCentre	−0.1157	0.0221	***	1.4357	−0.0815	0.0178	***	1.4357
	ln(Dis_TouristAttraction)	−0.0900	0.0212	***	1.3136	0.0559	0.0171	**	1.3136
	ln(Dis_Recreation)	−0.0538	0.0194	**	1.0993	−0.0110	0.0156		1.0993

(continued)

Table 10.2 (continued)

Main category	Indicators	Model 1 ln(Den_Check-in)				Model 2 ln(Den_Review)			
		Beta	Std. error	Sig	VIF	Beta	Std. error	Sig	VIF
Distance to transit	Dis_ Metro	−0.0236	0.0194		1.0989	−0.0119	0.0156		1.0989
	ln(Dis_Bus)	−0.1077	0.0206	***	1.2437	−0.0310	0.0166		1.2437
Control variable	ln(Den_Pop)	0.0454	0.0193	*	1.0875	0.1083	0.0155	***	1.0875
	Adjust R^2	0.201				0.481			

Note For each model, the table reports its predictive power (adjusted R^2). The coefficients (beta) in the regression results were standardized. For statistical significance, we used the following notation: $^*p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

In addition, similarities and differences in the spatial preferences revealed by the two types of online activities were presented in the results.

The similarities were reflected in the density and destination accessibility variables. All density and most design variables were positively associated with the dependent variable in both models. In contrast, all diversity and distance to transit variables and destination accessibility variables were negatively associated. This result showed that places with higher functional density, better design, lower functional diversity, and closer proximity to potential destinations for activities and transit were preferred, which suggested that even users engaging in online activities have apparent spatial preferences. To note that the conclusion of mixed-use locations seems to contradict some previous studies (Ye et al. 2018; Sung et al. 2015), which implied that some built environment variables positively associated with offline activities might have different or even opposite relationships with online check-ins and reviews. Our results provide an alternative perspective on the relationship between online and offline activities.

Considering the differences, the distance to transit variables was more significant in Model 1, while the diversity and design variables had higher significance in Model 2, suggesting that online check-in activities are more closely associated with places that are more convenient in terms of transit connections than with places with higher functional diversity or better design, while the associations for online reviews are the opposite, being more common in locations with higher functional diversity. Besides, for the two models, the distribution of the explanatory power of the variables was different: the density of education services, financial services, sports facilities, and public services and the distance to the city centre, to tourist attractions and bus stops each explained 8% to 11% of the variation in the dependent variable in Model 1, but there were no variables with extraordinarily high explanatory power. However, the density of catering services, retail services, and public services and the diversity of functions could explain more than 20% separately of the variance in Model 2, indicating that a few spatial factors play a decisive role in online reviews, but the factors associated with check-ins are not obvious enough.

10.3.3 Robustness Tests

To verify the validity of the results, we applied the RF method by randomly splitting the dataset for both models to create a training set (75% of the data) and a test set (25% of the data) and then used tenfold cross-validation to run the RF regression analysis. We then selected the optimal model with the smallest root mean square error (RMSE) value and compared its adjusted R^2 value with that from the OLS method (Table 10.3). The results showed that the regression relations for both dependent variables were stronger in the RF model than in the OLS model. These built environment elements can explain a total of 20.2% of the variance in Weibo check-ins and 50.6% of the variance in Dianping reviews on all street blocks. Overall, these results are similar to the previous results from the OLS models, suggesting the study results' robustness.

Table 10.3 Comparison of results between OLS and random forest

Dependent Variable	Adjusted R^2 (OLS)	Adjusted R^2 (Random Forest)
ln(Den_Check-in)	0.201	0.202
ln(Den_Review)	0.481	0.506

10.4 Conclusions and Discussion

10.4.1 Concluding Remarks

The advent of the mobile Internet has provided people with the possibility to conduct online activities anywhere, anytime, and in multiple ways. Online activities help people form new lifestyles and become an essential and substantial part of people's activities in this era. However, whether and how online activities are associated with the built environment has not been fully discussed. To elevate the discussion on the spatial preferences revealed by online activities and compare the differences across different types of online activities, we selected Weibo check-in data and Dianping review data to capture online social activities, and applied the five Ds to depict the built environment. This research identified relationships among these factors and revealed how they vary across different activities. We used Chengdu, the earliest Internet celebrity city in China, as the study area, and employed an OLS model to conduct the regression analysis and the RF method to verify the results. The results distinguished the spatial preferences of those engaged in these two types of activities and identified the similarities and differences.

The results proved the relevance of built environment elements to online activities. Compared with other indicators, the functional density indicators were the most significant in both the online check-in and review models. Moreover, this study also identified differences in spatial preferences of those who engage in these two types of online activities. For the Weibo check-ins, the destination accessibility and distance to transit variables were highly significant. While for the Dianping reviews, places with higher functional diversity and better design were preferred. Moreover, the research results also identified the spatial dependence of these two types of activities overall. The R^2 in the Dianping review model, which was higher than that in the check-in model, implied a closer relationship between online reviews and built environment elements.

10.4.2 Potential Contribution

Compared with other explorations of urban activities and the built environment assisted by the new data environment, this research considered online activities to be a remarkable phenomenon created by the mobile Internet and quantitatively examined the spatial preferences they reveal. Broader concerns from online activity perspectives have allowed for an in-depth understanding of contemporary cities' complexity and provided new opportunities to integrate cyberspace and city space (Lorente-Riverola and Ruiz-Sanchez 2018). For example, there were many claims such as "the death of distance/geography" in the late 20th and early twenty-first centuries (O'Brien 1992; Cairncross and Cairncross 1997; Drucker and Gumpert 2012), most of which claimed that ICTs would cause the decentralization and dispersion of activities (Dadashpoor and Yousefi 2018). In this study, the results from the Weibo check-in model partly supported this hypothesis. However, the results from the Dianping review model still implied the importance of geographic proximity. Although both are new social activities generated by the Internet, their relationships with urban spaces differ, reflecting the city's increasing complexity. These results also suggested that the relationship between cyberspace and urban space is not a zero-sum game. Some online activities still depend on urban space features, such as their functions, distances, and density. With this change in perspective from the traditional view of spatial-social activities to the new view of online activities, the scope for social production in urban spaces will expand.

The findings in this research can also help in future-oriented urban planning, design, and governance. Online activities such as E-WoM and location sharing have been verified to facilitate offline activities (Berger 2014; King et al. 2014), which means that places with more reviews and shared tags can accelerate offline activities, thus promoting urban vitality. This study showed that the functional density indicators were more strongly associated with online activities than other indicators, which reflected the greater importance of urban functions in social media users' minds. Therefore, urban governors or designers could pay more attention to those urban functions that stimulate online activities, thus encouraging people to engage with offline activities and make urban spaces more vibrant.

10.4.3 Limitations and Next Steps

Several limitations represent opportunities for further exploration. First, this study only explored two types of online activities, and additional different activities (including online and offline activities) could be introduced in further studies. Second, the similarities and differences in the spatial preferences between individuals engaging in online activities and those engaging in offline activities should be explored to improve the integration of offline and online activities through fine-scale designs. Third, urban activities are usually time-dependent and vary significantly across different periods. However, this study did not consider these online activities' time dimensions. Information about online activities and their different usages at different times should be explored in future studies. Moreover, similar analyses should be undertaken in other megacities in China or other countries to provide a "big picture" and generate universal value.

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