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User-generated content affects urban park use: Analysis of direct and moderating effects

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A R T I C L E I N F O

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A B S T R A C T

Urban parks contribute to sustainable urban development by bringing various social and environmental benefits; understanding the factors influencing park use is important for informing evidence-based park design and intervention. Although there are increasing number of studies using user-generated content (UGC) as a proxy of park use, few studies have examined how UGC influences park use. Therefore, we selected 221 urban parks in Guangzhou and Shenzhen, China, with multisource geographic data and collected 153,479 UGC from influential social media platforms. We discovered that UGC sentiment and park use were positively correlated, which was moderated by UGC exposure. In addition, park shape, vegetation and water coverage, land cover mix, parking lot density, and surrounding socioeconomic status, had indirect effects on park use via UGC sentiment. Solid evidence supports that UGC may affect park use because the spurious relationship arising from unmeasured confounders may not be moderated by UGC exposure. We recommend that UGC should be more carefully used as a proxy; its effect should be considered in future studies. In addition, we propose a tentative theoretical framework associating park use, UGC, and other key factors. This research provides a reference for future research and optimizing park use in the modern digital society.

1. Introduction

Urban parks, as a significant component of the urban natural infrastructure, provide a variety of social, health, and environmental benefits, which may help meet sustainable and nature-based urban development goals (Liu et al., 2023; Lu, 2019). Such benefits for city dwellers include reducing heat and noise, decreasing stress, facilitating physical activity, and promoting social interaction (Donahue et al., 2018; He et al., 2022; Lu, 2019). Thus, understanding how parks are used and why some are popular is crucial for informing evidence-based park planning and design and promoting park use and the associated benefits (Chen et al., 2018; Lu, 2019; Wu et al., 2023; Zhang and Zhou, 2018). A number of physical and social environmental elements of parks and surrounding areas, such as park size, accessibility, and safety, could influence park use (Chiang and Li, 2019; Hamstead et al., 2018; Lyu and Zhang, 2019).

According to recent studies, user-generated content (UGC) on social media sites has been widely employed to measure park use or user sentiments about parks. To be specific, the number of geotagged UGCs about a park is typically used to represent the relative number of users of that park (Li et al., 2020; Lu et al., 2021), while park visitors' experiences and sentiments are commonly assessed through analysis of the UGC text (Huai and Van de Voorde, 2022; Kong et al., 2022; Prakash et al., 2019; Roberts et al., 2019; Roberts, 2017).

Although UGC is omnipresent in this digital age, its independent effect on park use has not received much research attention. UGC is currently widely available: More than 4 billion users worldwide produced or viewed UGC on social media in 2022; approximately 25 % of these users were Chinese users (1.02 billion) (Statista, 2023). With UGC, park visitors can share their experiences with others, and potential

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visitors can seek information and comment on others' experiences. Thus, UGC can be regarded as an asynchronous and many-to-many medium for spreading park-related electronic word-of-mouth (Chen et al., 2014), which may inspire potential visitors' travel intentions or affect their decisions. Therefore, it is plausible that the UGC of urban parks also independently affects park use.

Indeed, UGC has been proven to affect various aspects of urban residents' everyday lives (Bak-Coleman et al., 2021; Castells, 2011) and has a significant impact on spatial decisions and activities, such as decision-making regarding tourism (Chen et al., 2014; Cuomo et al., 2021; Filieri and McLeay, 2014; Narangajavana Kaosiri et al., 2019). Because prospective visitors cannot know the quality of their trips before taking them, referring to UGC for travel planning has become a typical method of minimizing risk (Narangajavana Kaosiri et al., 2019). As UGC is typically generated voluntarily and independently by previous tourists, it is considered trustworthy for assisting prospective tourists in making travel plans and decisions, especially those regarding destination-specific trips and comparisons of multiple destinations (Filieri and McLeay, 2014; Zhang et al., 2021). In addition, positive and well-designed UGC may increase citizens' intention to visit destinations (Liu et al., 2019). Citizens may be unconsciously influenced by UGC content, such as beautiful scenes and descriptions of impressive experiences, which may lead to the development of travel intentions and expectations, thus prompting travel decisions (Narangajavana Kaosiri et al., 2019).

However, the main factors that affect park use in the contemporary digital world may be overlooked if the relationship between UGC and the use of urban parks is not fully examined. Our study was an initial attempt to examine UGC's effect on park use and establish related relationships.

1.1. Physical and social factors known to influence park use

Extensive research has used field observation, survey, and big-data approaches to examine the factors that influence urban park use (Chiang and Li, 2019; Donahue et al., 2018). Field observation and surveys are indispensable for obtaining fine-grained park use data but have several disadvantages. First, field observation is labor-intensive and time-consuming. Hence, it generally provides limited spatial coverage and small sample sizes, and the generalizability of the observed data is uncertain (Cohen et al., 2016). Second, survey data are prone to recall and social desirability biases. The survey participants may misremember their behavior when using a park (Donahue et al., 2018). Given these limitations, recent studies have quantified park use on the basis of volunteered geographic information (VGI) (e.g., geo-tagged UGC on social media) (Wilkins et al., 2021) or location-based service (LBS) data (e.g., Google Community Mobility Reports, Baidu Heatmap data, or mobile phone signaling data) (Chen et al., 2018; Guo et al., 2019). Such big data can provide a perspective that allows researchers to simultaneously assess the spatiotemporal distributions of park use on a large scale.

According to evidence from field observation, surveys, VGI, and LBS data, the three major types of factors affecting park usage are park attributes, the surrounding environmental attributes, and accessibility (Chen et al., 2018; Chiang and Li, 2019; Hamstead et al., 2018; Li et al., 2020).

First, park attributes, including size, shape, maintenance, and attractiveness (e.g., vegetation coverage, open water area, and diverse land cover), positively affect how frequently city residents visit parks (Chen et al., 2018, 2022; Hamstead et al., 2018; Li et al., 2020). For instance, a park with abundant greenspace and water bodies, diverse landscape attributes, and complex shapes with better connections to the surroundings may be attractive to visitors (Li et al., 2020). Second, because high accessibility enables residents to visit parks easily, it is critical to increase park use (Tang et al., 2021). The accessibility of urban parks is usually assessed using variables related to transportation infrastructure, including the density of public transit stops, parking lots, and streets and the degree of centrality of a park (Chen et al., 2018; Li et al., 2020). Third, well-designed environmental characteristics surrounding a park can also promote its use, and such characteristics include a favorable land-use mix and service facilities (Guo et al., 2019; Li et al., 2020). Other social attributes of the environment surrounding a park, such as dense population and high socioeconomic status (SES) in nearby neighborhoods, may also contribute to frequent park use (Donahue et al., 2018; Li et al., 2020). Thus, the first three hypotheses are:

H1. : *Park attributes have positive effects on park use.*

H2. : *Park accessibility has positive effects on park use.*

H3. : *Attributes of the surrounding environment have positive effects on park use.*

1.2. Factors affecting the sentiment of UGC regarding urban parks

Physical and social factors regarding urban parks have various effects on visitors' sentiments (Kong et al., 2022). Studies have widely employed UGC text as a proxy for the sentiment of park visitors (Cheng et al., 2021; Kong et al., 2022; Marchi et al., 2022; Wang et al., 2021) and discovered that accessibility, park attributes, and attributes of the surrounding environment may affect visitors' sentiment and experiences (Huai and Van de Voorde, 2022; Kong et al., 2022; Zhu et al., 2021).

Park attributes (e.g., a natural environment with greenspace and water bodies) play an essential role in boosting the positive sentiments of park visitors through the following mechanisms. First, greenspaces can mitigate the impact of hostile environments, including by reducing the effects of noise and urban heat islands (Cohen et al., 2014). Second, exposure to parks can alleviate people's stress, encourage a pleasant emotional state, and prevent negative sentiment (Hartig et al., 2014; Ulrich, 1984). Hence, an urban park with abundant and diverse greenspaces and water coverage can improve the sentiment of park users by lessening the impacts of negative environmental factors and reducing stress (Huai and Van de Voorde, 2022; Kong et al., 2022).

Park accessibility is correlated positively with visitors' sentiments (Zhu et al., 2021). Long-time and inconvenient traveling may lower travelers' happiness and increase their stress (Zhu and Fan, 2018). Hence, poor park accessibility may decrease visitor sentiment. In addition, the attributes of the environment surrounding a park and the sentiments of park visitors are associated. Prospective visitors who live in a well-built surrounding environment with high SES may inherently have positive emotions (Buckley, 2020; Kong et al., 2022), resulting in more positive sentiments toward the park during their park visits. Thus, the following three hypotheses are proposed:

H4. : *Park attributes have positive effects on UGC sentiment.*

H5. : *Park accessibility has positive effects on UGC sentiment.*

H6. : *Attributes of the surrounding environment have positive effects on UGC sentiment.*

1.3. Hypotheses regarding the relationship between park use and UGC

UGC on social media is widely accessible to city residents during everyday activities (Cuomo et al., 2021). Via UGC, park visitors can share their park visit experiences and offer suggestions for other potential visitors, such as better walking and jogging paths and essential attractions. Prospective visitors can search park-related UGC for others' perceptions or experiences. In this case, UGC can be seen as a many-to-many and asynchronous medium that builds and disseminates electronic word-of-mouth about urban parks, which may facilitate or inhibit potential park visitors' travel intention and thus affect park use.

Although little evidence suggests that UGC affects park use, some attributes of UGC, including its sentiment and exposure, have been shown to affect citizens' decision-making, such as that regarding vacation selection (Zhang et al., 2021) and the consumption of tourism products (Filieri and McLeay, 2014; Liu et al., 2019). Specifically, the rating on UGC directly shows the overall sentiment of previous tourists, which can have a significant impact on decision-making (e.g., selecting hotels) when tourists are faced with multiple options (Filieri and McLeay, 2014). In addition, positive or negative text-based reviews in UGC may also affect tourists' decisions (Nisar and Prabhakar, 2018). According to classical prospect theory, people may overweight negative comments than positive comments in their decision-making (Tversky and Kahneman, 1981). Recently, natural language processing (NLP) has provided an opportunity to quantify the sentiment of text-based UGC, resulting in explicit large-scale evaluation of UGC sentiment (Kong et al., 2022; Marchi et al., 2022).

Furthermore, UGC exposure may increase the effects of UGC sentiment because greater exposure, meaning that more people have viewed the UGC, results in greater dissemination of park-related UGC. Studies have indicated that social media influencers who have high exposure could increase UGC exposure and influence visitors to be more inclined to visit specific destinations (Pop et al., 2021; Xu and Pratt, 2018).

Hence, our final two hypotheses are:

H7. *: UGC sentiment has a positive effect on park use.*

H8. *: UGC exposure moderates the relationship between park use and UGC sentiment. Specifically, high UGC exposure will magnify the influence of UGC sentiment on the use of urban parks, while low exposure will decrease it.*

1.4. Our study and conceptual model

In summary, understanding the factors influencing park use is essential for increasing park use and realizing park benefits. Although UGC has been frequently employed by recent studies (Cheng et al., 2021; Huai and Van de Voorde, 2022; Kong et al., 2022), few such studies have focused on its impact on park use.

Therefore, we proposed two conceptual models (Fig. 1) based on our literature review to untangle the complex relationships among park use, UGC, and other influencing factors. Model 1 (Fig. 1a) includes H1 to H7. Although we controlled for known confounders that may affect both park use and UGC sentiment, H7 in Fig. 1a still cannot be fully interpreted by the UGC sentiment's effect on park use because of unmeasured confounders. For instance, the smell and the number of mosquitoes in a park may be unmeasured confounders that affect park use and UGC sentiment simultaneously. Results regarding the relationship of H7 may possibly be explained by the unmeasured confounders instead of revealing the genuine impact of UGC on park use (Imbens and Rubin, 2015). To further understand how UGC influences park use, we added H8, i.e., the moderating effect of UGC exposure on the association between park use and UGC sentiment, in Model 2 (Fig. 1b).

Higher UGC exposure for a park suggests that more visitors have viewed relevant UGC, which may in turn affect more viewers' decision-making. Therefore, if H8 were supported, the effect of H7 in Fig. 1b would be more likely to be reasonably interpreted as reflecting the influence of UGC sentiment on urban park use because the spurious relationship arising from the unmeasured confounders might not be moderated by UGC exposure.

2. Methods

2.1. Study design

Shenzhen and Guangzhou are the two most densely populated cities in China and are rapidly urbanizing. The census showed that these two cities had 17.56 million and 18.67 million residents, respectively, in 2022 (Guangdong Bureau of Statistics, 2022). Because of their abundant natural elements (e.g., rivers, lakes, and hills), Guangzhou and Shenzhen have urban parks that are diverse in terms of functions, type, and size.

Three criteria were employed for selecting sample parks in this study. First, the sample parks should have been open to the public for at least one year. Second, multisource geographic data should have been available for the parks. Third, the sample urban parks should have had their home pages on social media platforms. 221 urban parks were chosen after the selection process. The park boundaries were collected via the application programming interface (API) offered by Baidu Maps; satellite images from Google Earth were employed to verify their accuracy (Fig. 2).

We took temporal precedence into account in data collection to build models reliably (Spector, 2019). We collected park use data on warm and sunny days during two weekdays and weekends (November 27,

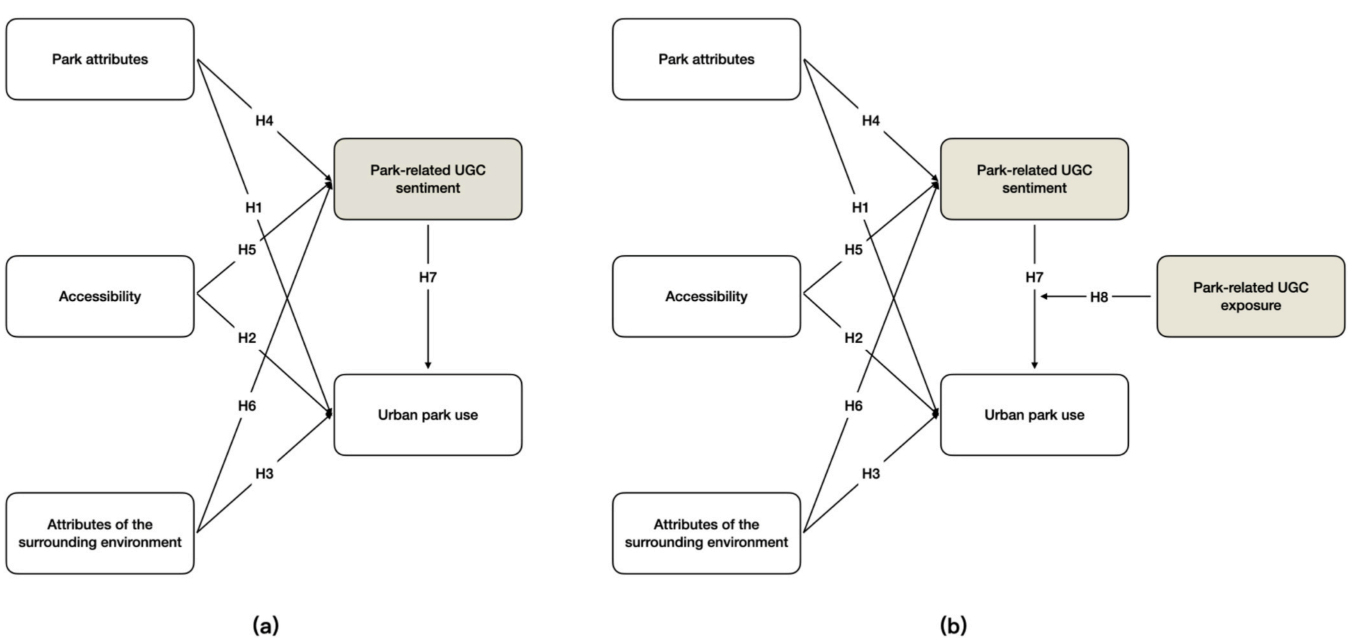
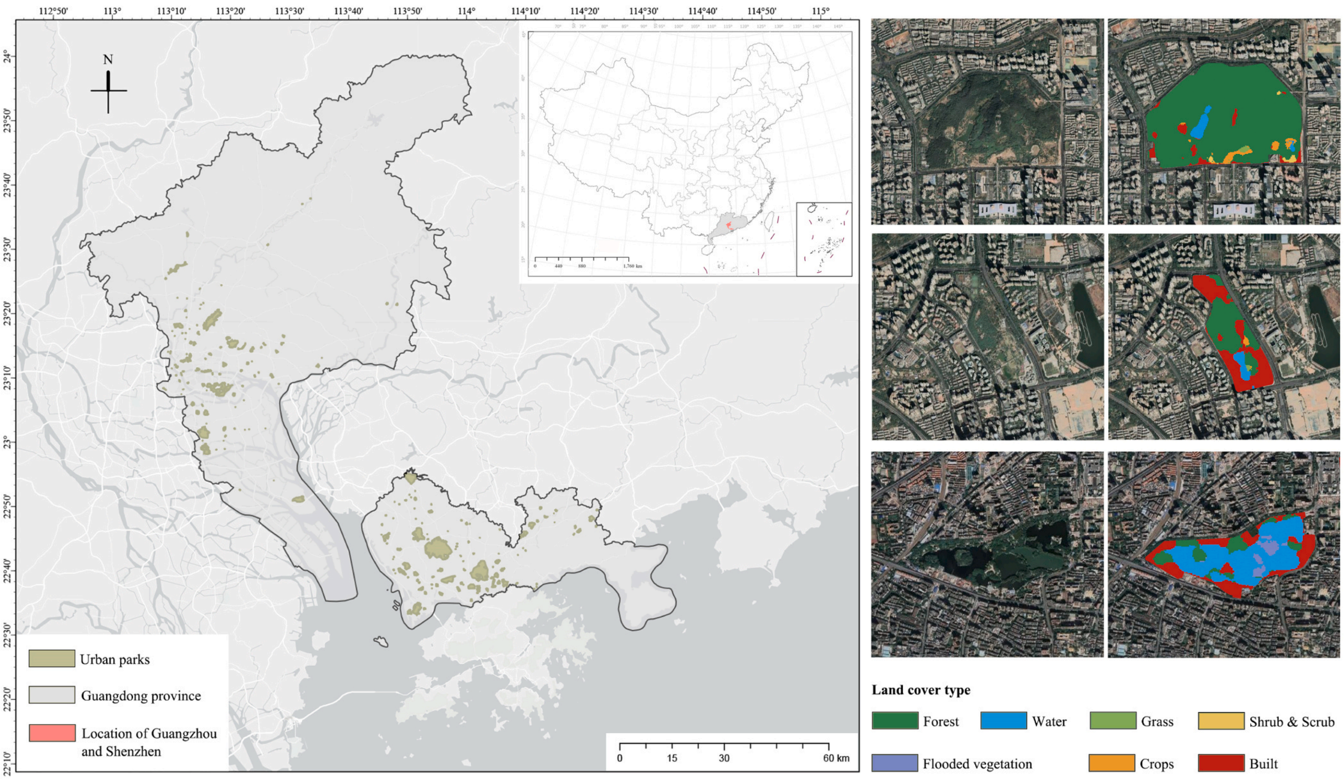


Fig. 1. Conceptual model relating park attributes, accessibility, attributes of the surrounding environment, park use, and UGC. (a) Model 1 includes H1 to H7; (a) Model 2 includes H1 to H8.



(a) (b)

Fig. 2. Mapping of sample parks in Shenzhen and Guangzhou, China. (a) Location of urban parks; (b) Land cover types of urban parks.

2021, to November 30, 2021), while the park-related UGC was collected before the data collection period of park use (i.e., before November 27, 2021). At the time of data collection, these two cities had not imposed any COVID-19-related social segregation orders restricting people from visiting the parks.

2.2. Variables

2.2.1. Calculating urban park use using Baidu Heatmap

LBS data from companies such as Google and Baidu offer an alternative means of detecting the spatiotemporal distributions of urban residents. Baidu is a Chinese technology company providing multiple popular services, such as search engine and map applications, which generate 6 billion responses per day (Li et al., 2019). Baidu Heatmap is a tool that illustrates the spatial distribution of all individuals using Baidu products (e.g., Baidu Maps and Baidu Search). Because LBS data can reflect real-time user density, Baidu Heatmap data have been frequently employed as proxies (e.g., for population density or park use) in various types of urban research and have been demonstrated to be accurate and reliable (Fan et al., 2021; Li et al., 2021, 2019; Lyu and Zhang, 2019).

We referenced the experimental design and data processing procedures of previous studies (Fan et al., 2021; Lyu and Zhang, 2019): we sampled park use data from Baidu Heatmap and collected data from 7:00–21:00 between 27th November and 30th November, 2021 (Saturday to Tuesday). The Baidu Heatmap data were retrieved every 2 h during the data collection periods, resulting in 32 heatmaps with 1-m spatial resolution. The heatmap values of each pixel within the park boundaries were used to evaluate the relative number of visitors in the park (Lyu and Zhang, 2019) in ArcGIS Pro 2.8.1. Park use data for each park were calculated as the sum of the heatmap data. The park use data are described in Supplementary Material 1.

2.2.2. UGC variables

Four UGC datasets were obtained from four influential Chinese social media sites: Sina Weibo (SW), Tiktok, Kuaishou, and Dazhong Dianping (DZDP). To simulate how individuals browse UGC by using web browsers or apps, we employed the Python Scrapy package to crawl the UGC visible to users on the platforms. All park-related UGC on the platforms between November 13 and November 26, 2021, was collected, resulting in 302,698 UGC. After data cleaning procedures, 153,479 UGC were retained for this study. Details regarding the UGC collection and description are provided in Supplementary Material 2.

To accurately evaluate UGC sentiment from different perspectives, we assessed the park-related UGC sentiment by using five observed variables (UGC rating of DZDP, UGC sentiment of SW, DZDP, Tiktok, and Kuaishou). Using a latent variable generated from these five observed variables can reduce measurement error and improve estimation accuracy (Diamantopoulos et al., 2012). In detail, we collected park ratings on UGC of DZDP because they can directly reflect people's emotions or preferences about the park. In addition, we evaluated the emotions underlying UGC through NLP-based sentiment analysis. Sentiment analysis is a process in which a computer evaluates subjective text with overtones of emotion to determine whether the text has a positive or negative emotional orientation. The pre-trained sentiment analysis model offered by the Baidu NLP (https://ai.baidu.com/easydl/nlp) was employed; this model has been widely used to analyze the sentiment of Chinese UGC in urban studies (Cheng et al., 2021; Huai and Van de Voorde, 2022; Kong et al., 2022). Sentiment values are in the range of 0–2 (where 0 represents "extreme negative sentiment" and 2 represents "extreme positive sentiment"). We validated the method of sentiment analysis (details in Supplementary Material 3), revealing that our sentiment analysis has high accuracy (Table S1). Therefore, we performed sentiment analysis by extracting the texts from the park-related UGC. For UGC in video format, we used text descriptions. Finally, we calculated the values of five observed variables for measuring UGC sentiment, including UGC park rating on DZDP and average sentiment scores of UGC on SA, DZDP, Tiktok, and Kuaishou, respectively.

Because not all social media platforms provide view count data for UGC, we employed the comment count as a proxy for the number of views, which was chosen because people typically read UGC before commenting. To indicate the average exposure of each park-related UGC, we calculated the average number of comments on UGC per park. Following is the calculation of UGC exposure:

$$EXPO = \frac{\sum_{i=1}^{s} C_i}{\sum_{i=1}^{s} Q_i}$$

Where EXPO is UGC exposure, s is the number of UGC datasets, C_i is the total number of comments on UGC for parks in the ith dataset, and Q_i is the total number of UGC for parks in the ith dataset.

For parks that lacked park-related UGC, we assigned a sentiment score of 1, indicating neutral sentiment, to the UGC sentiment on SA, DZDP, TikTok, and Kuaishou, and a park rating of 3 on DZDP (which ranges from 1 to 5), representing a neutral rating. The UGC exposure value for such parks was set to 0.

2.2.3. Other variables

To assess the factors influencing park use and UGC, we collected data of satellite images, roads, point of interest (POI), and house prices and calculated the variables of park characteristics, accessibility, and characteristics of the surrounding environment. In detail, we evaluated 13 variables, including 1) five variables – park area, normalized difference water index (NDWI), landscape shape index (LSI), normalized difference vegetation index (NDVI), and land cover entropy of park – to describe the park attributes; 2) four variables – road density, parking lot density, public transit density, and distance to center – to describe accessibility; 3) four variables – surrounding POI density, surrounding POI entropy, SES, and population density – to describe attributes of the surrounding environment. Furthermore, we generated an "IfTourismSite" variable based on the directory of tourism sites (Guangzhou Culture, Radio, Film and Tourism Bureau, 2022; Shenzhen Culture, Radio, Film and Tourism Bureau, 2023) to determine whether the sampled parks have been listed as tourist attractions and control the influence of tourist site status on the results. And Table 1 illustrates the descriptive statistics of the variables. Supplementary Material 4 presents the details of the variable calculation.

2.3. Statistical analysis

To examine our hypotheses, we employed latent moderated structural equation (LMS) to analyze the direct and moderating effect of UGC on park use. LMS is an effective approach for investigating the complicated association underlying a set of variables and examining the moderation effects (Maslowsky et al., 2015; Sardeshmukh and Vandenberg, 2017). In LMS, abstract concepts (e.g., UGC sentiment) can be measured as a latent variable via multiple observed variables to effectively reveal the complex direct and moderation effects among variables (Maslowsky et al., 2015); it also enhances the precision and credibility of variables by considering the effect of measurement errors. In addition, the advantages of LMS over other regression-based moderation methods are that it not only effectively and concurrently assesses latent

Table 1
Descriptive statistics of variables in the models.

Variables	Description	Proportion / Mean (SD)	Standardized loadings	Cronbach's alpha
Park attributes				
Park area	The area of urban parks (km^2)	0.678 (2.549)		
Landscape shape index (LSI)	A measure of the park form	0.733 (0.134)		
Normalized difference vegetation index (NDVI)	A measure of vegetation coverage	0.627 (0.136)		
Normalized difference water index (NDWI)	A measure of water coverage	-0.016 (0.041)		
Land cover entropy	A measure of land cover mix in an urban park	0.399 (0.349)		
Accessibility				
Road density	The density of road in the surrounding area (m/m^2)	0.009 (0.005)		
Public transit density	The density of public transit in the surrounding area, including bus and metro stations (POI number/km^2)	5.864 (4.668)		
Parking lot density	The density of parking lots in the park and surrounding area (POI number/km^2)	9.055 (15.986)		
Distance to center	Distance between an urban park and urban center (km)	18.065 (11.628)		
Attributes of the surrounding environment				
POI density	A measure of development status by POI density in the surrounding area (POI number/km2)	513.703 (411.816)		
POI entropy	A measure of land use mix by POI entropy in the surrounding area	0.799 (0.075)		
Population density	The population density in the surrounding area (Household number/ km^2)	3957.791 (4779.938)		
SES	The average flat price in the surrounding area (1000 CNY)	32.455 (28.939)		
Park-related UGC				
UGC sentiment	The UGC sentiment of urban parks			0.788
Park rating of DZDP	The rating of urban parks on DZDP UGC	4.041 (0.692)	0.906	
UGC sentiment of SW	The sentiment of urban parks on SW UGC	1.455 (0.305)	0.748	
UGC sentiment of DZDP	The sentiment of urban parks on DZDP UGC	1.540 (0.363)	0.689	
UGC sentiment of Tiktok	The sentiment of urban parks on Tiktok UGC	1.833 (0.336)	0.496	
UGC sentiment of Kuaishou	The sentiment of urban parks on Kuaishou UGC	1.759 (0.413)	0.522	
UGC exposure	The exposure of urban parks per UGC online	311.588 (1116.116)		
Control variable				
IfTourismSite	If the sample parks are listed on the directory of tourism sites			
Tourism site		2.71 %		
Not tourism site		97.29 %		
Urban park use				
Park use value	The value of urban park use with logarithmic transform	0.421 (0.194)		

interaction effects in a single model. (Maslowsky et al., 2015), but it also produces unbiased parameter estimates that are robust to the latent variables' nonlinearity and deviations from normality (Klein and Moosbrugger, 2000).

Before developing LMS, the potential spatial effect was examined. The results of Moran's I test for model residuals ($p > 0.05$) and Lagrange multiplier pre-test ($p > 0.05$) indicated no significant spatial effect in our model (Anselin et al., 2010). Next, the variance inflation factor (VIF) test was used to eliminate potential multicollinearity within the variables. Every variable's VIF value is less than 4, indicating no significant multicollinearity in the model (O'brien, 2007). The natural logarithm was taken for park use and UGC exposure to ensure conformance to a normal distribution.

To better examine our hypotheses, we inverse the sign of LSI and distance to center values (positive to negative) in the LMS model to keep the positive and negative signs consistent with other factors. Thus, the high distance to center value represents a park close to the center; the high LSI value represents the more complex shape of a park.

Then, Cronbach's alpha and confirmatory factor analysis (CFA) were employed to evaluate the validity and reliability of the variables. After that, the chi-square statistic ($\chi2$) (Hirotsu, 1986), the Root Mean Square Error of Approximation (RMSEA) (McDonald and Ho, 2002), Standardized Root Mean Square Residual (SRMR) (Hu and Bentler, 1999), and Comparative Fit Index (CFI) (Hu and Bentler, 1999) were employed to examine the model fit.

At last, we estimated two hypothesized models based on LMS approach. Model 1 served as a baseline model, including H1 to H7 without interaction estimates. Model 2, including all hypotheses (H1 to H8), was then evaluated using the full LMS model. We create an interaction term between UGC sentiment and UGC exposure (sentiment * exposure) to assess the moderation effect in Model 2. Following previous studies, we used the two-step method (Maslowsky et al., 2015; Sardeshmukh and Vandenberg, 2017) to assess the model fit of the full LMS model. First, the $\chi2$, CFI, RMSEA, and SRMR were used to examine the baseline model (Model 1)'s model fit. If the baseline model fits well, the log-likelihood ratio test (D) will assess the relative fit between the baseline model and the full LMS model (Model 2), calculated as follows. The Chi-square distribution was then employed to assess the significance (Sardeshmukh and Vandenberg, 2017).

$$D = -2[(loglikelihood\_Model1 - loglikelihood\_Model2)]$$

To test mediation effects, we used the bootstrapping technique (1000 samples) (Lau and Cheung, 2012; Preacher and Hayes, 2008) to assess the significance of mediation effects between the predictor and outcome. By assessing bootstrapped confidence intervals (CIs), power issues caused by asymmetric and other non-normal samplings of an indirect effect could be avoided (MacKinnon et al., 2004).

All statistical analyses were performed in R v4.0.5 and MPlus 8.1.

3. Results

3.1. Results of model fits

The model fit test showed that our models had a high degree of model fitness. First, the fitness of Model 1 was evaluated. We regarded the model fit to be adequate when it met the standard cut-off values of fit indices with $\chi2/DF \leq 5$ (Hirotsu, 1986), $CFI \geq 0.90$, (Hu and Bentler, 1999), $SRMR \leq 0.08$ (Hu and Bentler, 1999), and $RMSEA \leq 0.08$ (McDonald and Ho, 2002). The CFA of UGC sentiment showed adequate fit ($\chi2/DF = 3.304$; $CFI = 0.985$; $SRMR = 0.024$); all loading of observed variables was significant to UGC sentiment ($p < 0.001$) and varied from 0.496 to 0.906, while Cronbach's alpha is 0.788, showing good validity and reliability for UGC sentiment (Table 1). Then, the structural model was assessed. Model 1 showed a good fit via the matching degree analysis ($\chi2/DF = 3.230$; $CFI = 0.913$; $RMSEA = 0.074$; $SRMR = 0.046$) (Table 2).

Table 2
Fitting test of the LMS model (* $p < 0.05$). The results indicated that Model 1 and Model 2 had an adequate fit.

Measure	*Result of Model 1*	*Result of Model 2*	*Suggested value*
AIC	1254.783	1251.952	
H0 (log-likelihood value)	–582.392	–578.976	
DF	45	47	
$\chi2$	145.369		
P-value	<0.001		<0.05
$\chi2$/DF (Hirotsu, 1986)	3.230		≤5
CFI (Hu and Bentler, 1999)	0.913		>0.90
RMSEA (McDonald and Ho, 2002)	0.074		<0.08
SRMR (Hu and Bentler, 1999)	0.046		<0.08
ΔAIC		–2.831	<0
Log-likelihood ratio test		0.033*	<0.05

Since Model 1 (baseline model) showed adequate fit to the data, we tested the model fitness of Model 2 (full LMS model). As shown by the smaller AIC ($\Delta AIC = -2.831$) and log-likelihood ratio test ($p < 0.05$) (Maslowsky et al., 2015; Sardeshmukh and Vandenberg, 2017), Model 2 showed better fitness than the baseline model, suggesting that the fitness of Model 2 was adequate. The standardized path coefficients of Model 2 are illustrated in Fig. 3.

3.2. Hypothesis testing

The results of LMS are reported in Table 3. The effect of park attribute variables, including park area, LSI, NDVI, NDWI, and land cover entropy, were all significant, supporting H1. Among them, LSI, NDVI, and NDWI had significant direct and indirect effects on park use via sentiment, while NDVI had the largest total effect (0.347) on park use. Only land cover entropy had no direct effect but had a significant indirect effect on park use. In contrast, only one variable with a significant indirect effect (parking lot density) supported H2; two variables supported H3 (POI entropy and SES), respectively.

For the park sentiment, almost all park attribute variables, including LSI, NDVI, NDWI, and land cover entropy, had significant positive effects on UGC sentiment, and thus H4 was supported. In contrast, only parking lot density among the accessibility variables and SES among the surrounding environment attributes exhibited positive relationships with UGC sentiment, partly supporting H5 and H6, respectively.

It is worth noting that UGC sentiment had a significant positive effect on park use (0.402, $p < 0.001$), supporting H7. Furthermore, the significant results of the interaction term ($p < 0.05$) suggest that UGC exposure significantly moderated the association between park use and UGC sentiment, hence supporting H8.

3.3. Interaction of UGC sentiment and exposure

To identify the significant interaction effects, we examined the relationship between UGC sentiment and park use at low and high levels of UGC exposure via slope analysis (Fig. 4) (Aiken et al., 1991). We found that park use was positively related to UGC sentiment with both high UGC exposure ($\beta = 0.485$, $p < 0.001$) and low UGC exposure groups ($\beta = 0.325$, $p = 0.007$). The steeper slope for high UGC exposure group indicated that UGC sentiment had a greater effect with high exposure group compared to low exposure group on park use. In addition, the difference in park use between the high and low exposure groups was greater at low sentiment values. This indicates that, for parks with negative UGC sentiment, UGC exposure leads to a larger disparity in park use, whereas such disparity diminishes for parks with positive UGC sentiment.

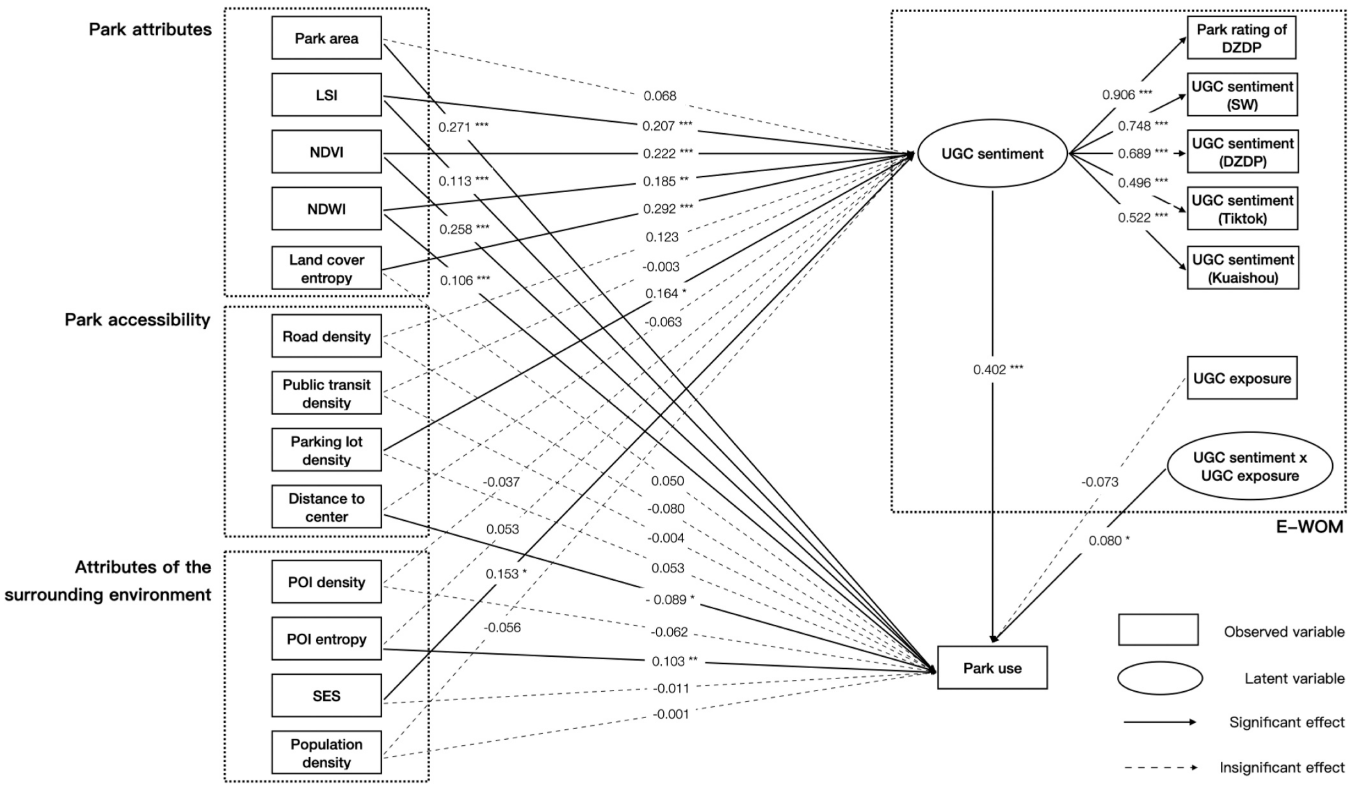


Fig. 3. Standardized path coefficients of Model 2 (* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$). UGC sentiment had a significant effect on park use (0.402, $p < 0.001$), and UGC exposure significantly moderated the relationship between UGC sentiment and park use.

4. Discussion

4.1. Interpretation of key findings

Strong evidence confirms that several physical and social factors, including accessibility, park characteristics, and attributes of the surrounding environment, may affect park use. However, few studies have focused on the effect of UGC on park use, despite UGC being widely employed as proxies of park use in existing park-related studies. Thus, we applied LMS modeling to analyze how park-related UGC influences park use and validate our conceptual model linking park use, UGC, and their influencing factors. To be specific, we draw three key findings.

4.1.1. Relationship between park use and UGC

To begin with, park-related UGC could affect park use. Strong support comes from the moderating effect of UGC exposure on the relationship between park use and UGC rather than from the direct relationship between park use and UGC sentiment. Although we found a significant and positive effect of UGC sentiment (0.402, $p < 0.001$) on park use, we could not rule out the possibility that this effect was caused by unmeasured confounders (e.g., smell or mosquitoes in a park). Such unmeasured confounders might affect both park use and UGC sentiment, resulting in a spurious relationship (Imbens and Rubin, 2015). However, UGC exposure's significant moderating effect on the link between UGC sentiment and park use provides further evidence that UGC may affect park use. UGC exposure indicates the number of people who have read UGC. Thus, a UGC sentiment with high exposure tends to reach a larger audience than that with low exposure. The significant moderating effect of UGC exposure indicated that more potential park users are influenced by UGC sentiment with high exposure. Therefore, UGC sentiment may significantly affect park use because UGC exposure may not moderate such spurious relationships caused by unmeasured confounders.

Our finding concurs with previous studies regarding the association between UGC and the behavior of urban residents (Filieri and McLeay, 2014; Tsiakali, 2018; Zhang et al., 2021). The UGC, which consists of such "self-disclosure" of subjective information, is updated and shared with other users on a regular basis, and has evolved into a means of influencing residents' perceptions, feelings, and experiences (Zhang et al., 2021). Similarly, park visitors can share their experiences, observations, and feelings online, which contain information about visitors' motivation, perception of natural features, and satisfaction with urban parks (Oteros-Rozas et al., 2018). Hence, the park-related UGC from previous visitors may encourage or discourage prospective visitors' park use.

It is noteworthy that we found that a park with relatively negative UGC sentiment had greater variations in use because of UGC exposure. A park with negative UGC sentiment was used less when UGC exposure is higher. This may be because people are more likely to prioritize negative comments over positive ones (Tversky and Kahneman, 1981). Because the sentiment of park-related UGC is generally more positive, negative UGC is more likely to be noticed by prospective park visitors and may significantly affect their decision-making (Nisar and Prabhakar, 2018).

4.1.2. Association between UGC and its influencing factors

We observed that UGC sentiment was positively related to park attributes, including vegetation coverage, water bodies, and land cover mix. These findings align with those of other studies explaining that the park attributes may promote visitors' positive perception (Cheng et al., 2021; Kong et al., 2022). This result may be attributed to the environmental benefits of vegetation and water coverage (e.g., reducing the negative effects of urban heat islands and noise). Furthermore, a natural environment with a wide variety of landscape features may alleviate visitors' stress and restore their concentration (Cohen et al., 2014; Ulrich, 1984; Zhao et al., 2020). Research has indicated that landscape features and water bodies positively impact park users' physical and emotional recovery (Deng et al., 2020; Wang et al., 2016). In addition, we discovered that parks with more complex shapes had more positive UGC sentiment. This may be because a park with a more complex shape

Table 3
Standardized parameter estimates and effects on UGC and park use. * $p < 0.05$; * * $p < 0.01$; * ** $p < 0.001$.

Hypothesized paths	Model 1		Model 2					Hypotheses	
	Std. estimate (S.E.)	P-value	Std. estimate (S.E.)	P-value	Direct effect	Indirect effect (95 % CI)	Total effect		
Park area → Park use	0.268 (0.040)	<0.001***	0.271 (0.040)	<0.001***	0.271	–	0.271	Supported	*H1 Park attributes have positive effects on park use.*
LSI → Park use	0.126 (0.040)	0.002**	0.113 (0.040)	<0.004**	0.113	0.083 (0.052, 0.114)	0.196	Supported	
NDVI → Park use	0.251 (0.042)	<0.001***	0.258 (0.042)	<0.001***	0.258	0.089 (0.05, 0.128)	0.347	Supported	
NDWI → Park use	0.114 (0.037)	0.002**	0.106 (0.037)	<0.005**	0.106	0.074 (0.047, 0.101)	0.180	Supported	
Land cover entropy → Park use	0.046 (0.040)	0.243	0.050 (0.039)	0.198	–	0.117 (0.083, 0.151)	0.117	Supported	
Road density → Park use	–0.080 (0.042)	0.055	–0.080 (0.041)	0.054	–	–	–	Rejected	*H2 Park accessibility has positive effects on park use.*
Public transit density → Park use	–0.004 (0.037)	0.909	-0.004 (0.036)	0.916	–	–	–	Rejected	
Parking lot density → Park use	0.072 (0.044)	0.104	0.053 (0.045)	0.230	–	0.066 (0.030, 0.102)	0.066	Supported	
Distance to center → Park use	–0.089 (0.038)	0.021*	–0.089 (0.038)	0.018*	–0.089	–	-0.089	Rejected	
POI density → Park use	–0.067 (0.033)	0.059	-0.062 (0.033)	0.058	–	–	–	Rejected	*H3 Attributes of the surrounding environment have positive effects on park use.*
POI entropy → Park use	0.103 (0.036)	0.005**	0.103 (0.036)	0.004* *	0.103	–	0.103	Supported	
SES → Park use	0.004 (0.046)	0.921	-0.011 (0.045)	0.807	–	0.062 (0.022, 0.102)	0.062	Supported	
Population density → Park use	–0.002 (0.043)	0.970	-0.001 (0.042)	0.981	–	–	–	Rejected	
Park area → UGC sentiment	0.068 (0.061)	0.266	0.068 (0.061)	0.268	–	–	–	Rejected	*H4 Park attributes have positive effects on park-related UGC sentiment.*
LSI → UGC sentiment	0.210 (0.058)	<0.001***	0.207 (0.059)	<0.001***	0.207	–	0.207	Supported	
NDVI → UGC sentiment	0.224 (0.063)	<0.001***	0.222 (0.063)	<0.001***	0.222	–	0.222	Supported	
NDWI → UGC sentiment	0.185 (0.055)	0.001**	0.185 (0.055)	0.001**	0.185	–	0.185	Supported	
Land cover entropy → UGC sentiment	0.293 (0.057)	<0.001***	0.292 (0.057)	<0.001***	0.292	–	0.292	Supported	
Road density → UGC sentiment	0.123 (0.066)	0.062	0.123 (0.066)	0.061	–	–	–	Rejected	*H5 Park accessibility has positive effects on park-related UGC sentiment.*
Public transit density → UGC sentiment	–0.003 (0.059)	0.960	-0.003 (0.059)	0.959	–	–	–	Rejected	
Parking lot density → UGC sentiment	0.162 (0.069)	0.019*	0.164 (0.069)	0.018 *	0.164	-	0.164	Supported	
Distance to center→ UGC sentiment	–0.062 (0.061)	0.303	-0.063 (0.061)	0.304	–	–	–	Rejected	
POI density → UGC sentiment	–0.033 (0.052)	0.519	-0.037 (0.052)	0.478	–	–	–	Rejected	*H6 Attributes of the surrounding environment have positive effects on park-related UGC sentiment.*
POI entropy → UGC sentiment	0.053 (0.057)	0.351	0.053 (0.057)	0.351	–	–	–	Rejected	
SES → UGC sentiment	0.154 (0.072)	0.032*	0.153 (0.072)	0.033 *	0.153	–	0.153	Supported	
Population density → UGC sentiment	–0.054 (0.068)	0.427	-0.056 (0.068)	0.414	–	–	–	Rejected	
UGC sentiment → Park use	0.472 (0.057)	<0.001 ***	0.402 (0.062)	<0.001 ***	0.402	–	0.402	Supported	*H7 Park-related UGC sentiment has a positive effect on park use.*
UGC exposure → Park use			-0.073 (0.092)	0.425	–	–	–		*H8 Park-related UGC exposure moderates the positive relationship between UGC sentiment and park use.*
UGC sentiment * UGC exposure → Park use			0.080 (0.038)	0.035 *	–	–	–	Supported	
Control Variable									
IfTourismSite → Park use	0.041 (0.033)	0.215	0.041 (0.033)	0.218	–	–	–		

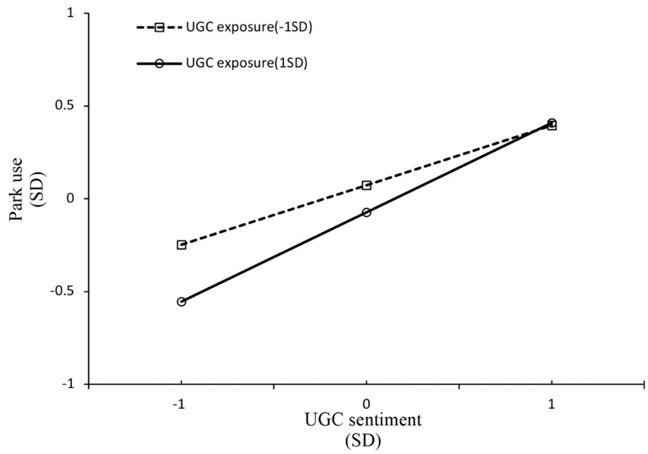


Fig. 4. Interaction of UGC sentiment with UGC exposure for predicting urban park use. The result indicated that UGC sentiment had a significantly stronger effect on park use with high-exposure group (β = 0.485) than in low-exposure group (β = 0.325).

is typically well-designed and has a better connection to its surroundings, which may positively impact the experience and sentiment of visitors.

Besides, only one accessibility variable (density of parking lot) showed a positive association with UGC sentiment, which indicated that parking lots might affect visitors' sentiment more than distance and public transit service. The significance of parking lot density might be attributed to the insufficient parking facilities in the two cities (Yang & Huang, 2017). Consequently, sentiment is more sensitive to changes in parking lot density. In contrast, public transit services are generally well-established in first-tier cities; the lack of variations in public transit density may lead to a weak link with UGC sentiment. We also found a significant relationship between SES and UGC sentiment; this may be because the visitors with higher SES who live near the park may inherently have more positive sentiment (Buckley, 2020; Kong et al., 2022).

4.1.3. Direct and indirect effects of influencing factors on park use

Our findings suggested that the main direct effects on park use were caused by park attribute variables, including park area, LSI, NDVI, and NDWI. Particularly, park areas had a significant association with park use, which is in line with park use research in other cities (Donahue et al., 2018; Zhang and Zhou, 2018). Larger parks typically offer more walking paths and diverse scenes, and thus, visitors tend to use larger parks more frequently than smaller ones when both are within an acceptable distance (Schipperijn et al., 2010; Zhang and Zhou, 2018). The finding of LSI being significant is consistent with the findings of recent research (Li et al., 2020) and indicated that parks with more complex and well-designed shapes tend to have better connections to the surrounding neighborhoods and hence are used more frequently (Li et al., 2020). Previous research also indicated that parks featuring abundant natural landscapes, including vegetation and water bodies, will attract more people (Donahue et al., 2018; Fan et al., 2021; Zhang and Zhou, 2018). Our findings, which corroborate the previous research, provide more proof of the significance of park attributes in promoting park use.

Moreover, although the land cover mix did not have a direct effect on park use, it had a significant indirect effect, indicating that it might influence park use through UGC. Indeed, land cover mix has been confirmed to be associated with the density of UGC photos (Tieskens et al., 2018) because the diverse combination of landscapes may attract people and allow them to take attractive photos. Thus, a desirable land cover mix of a park may attract visitors through UGC.

4.2. Implications

Upon being validated in further studies, our findings have some tentative theoretical contributions and implications for park planning and management.

In this modern digital society, people carrying digital terminals (e.g., smartphones and smartwatches) are all potential receivers and generators of digital information (Castells, 2011). Many people not only generate digital traces in their everyday lives (e.g., texts, images, tags, and shared places) but are also influenced by these data (Bak-Coleman et al., 2021). In both research and practice, UGC may help us understand which parks are the most used and how and why people use them (Hamstead et al., 2018). Furthermore, UGC may be an independent predictor of people's decisions to visit parks.

We believe that our study reveals a new phenomenon essential for informing academic research and park management. We proposed three recommendations. First, researchers should be cautious about using UGC as a proxy of park use; its potential effect on park use should be considered in future park-related studies. Second, UGC regarding urban parks, especially negative reviews, should be considered by park management. Promptly addressing issues raised by negative reviews may attenuate their negative impact on park use. Third, we recommend that park managers frequently post high-quality UGC (e.g., attractive landscape scenes or festival activities) on influential social media platforms to improve UGC sentiment and attract visitors. Also, park managers should increase the exposure of positive UGC to enhance the beneficial impact of positive UGC sentiment on the usage of urban parks.

Besides, various built environment variables, including park shape, vegetation, and water coverage, had significant effects on both park use and UGC sentiment, while the land use entropy of park, parking lot density, and SES of surrounding neighborhoods had significant indirect effects on park use. Thus, urban designers and policymakers should pay particular attention to the impacts of these variables on park use when designing new or improving existing parks in the future.

4.3. Limitations

Our study has some limitations. First, although Baidu Heatmap data have various advantages over survey data, such as a large sample size, time and cost-effectiveness, and minimal recall bias and social desirability bias, they are simply a proxy of park use and may overlook actual park use by people without smartphones or Baidu products. Also, it is difficult to collect individual factors (e.g., age or gender) from Baidu data. Thus, future research should combine Baidu Heatmap data with information from the surveys or site observation to address this limitation. Furthermore, although we followed existing studies and collected park use data in four days (two weekdays and two weekends) and aggregated the data to generate park use variables, it might lead to bias in measuring actual park use due to the short data collection duration. Therefore, future studies should employ a longer data collection period and analyze weekdays and weekends separately to validate our results. In addition, we obtained some results inconsistent with previous studies. For instance, our findings indicated that road density, public transit density, POI density, and population density did not exhibit significant effects on park use. However, previous studies have indicated the significance of these variables (Fan et al., 2021; Lyu and Zhang, 2019). Such inconsistency may be attributed to differences in the selected study areas. Studies have indicated that the relationship between influencing factors and park use often varies across diverse urban contexts and scales (Donahue et al., 2018). While previous studies have focused on areas within new first-tier Chinese cities (e.g., Nanjing or Wuhan) (Fan et al., 2021; Lyu and Zhang, 2019), our study area pertains to first-tier cities in China, characterized by higher population densities and economic conditions than previously studied cities. Hence, future studies should conduct in multi-regional or nationwide cities to validate the generalizability of the research findings. Additionally, we could not fully confirm the causal link between park use and UGC via the cross-sectional study design, though our moderation analysis offered some promising findings regarding such causal links. Their causal association should be further verified through natural experiments.

5. Conclusion

This is one of the first studies that investigated the direct and moderating effect of park-related UGC on the usage of urban parks. We found that UGC sentiment had a significant effect on park use; the exposure of UGC significantly moderated the relationship between UGC sentiment and park use. In addition, some park attributes, including park shape, vegetation coverage, and water coverage, play crucial roles in affecting both park-related UGC and park use. Our findings suggested that the park-related UGC may significantly influence urban park use in the modern digital society, which warrants adequate attention for park planning and management.

CRediT authorship contribution statement

Di Wei: Conceptualization, Methodology, Software, Writing - Original Draft. **Mengyang Liu**: Methodology, Software, Validation. **George Grekousis**, Writing- Reviewing and Editing. **Yuan Wang**: Conceptualization, Supervision. **Yi Lu**: Writing- Reviewing and Editing, Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.ufug.2023.128158.

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