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User-generated content may increase urban park use: Evidence from multisource social media data

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Abstract
Given the numerous health benefits that urban parks and greenspaces provide, it is critical to grasp the key factors that improve park use. Despite the pervasive impact of user-generated content (UGC) in modern society, little is known about the influence of UGC on park use. Therefore, this study examined the effect of UGC on park use based on 613,858 pieces of UGC related to the 251 urban parks in two metropolitans in China, Guangzhou and Shenzhen. After controlling for the confounders, the hierarchical linear regression revealed that the quantity, rating, sentiment, and exposure were significantly associated with park use. Then, we distinguished three distinct relationships between UGC variables and park use. We proposed that the effects of UGC rating, sentiment, and exposure were more reliable predictors of park use because bidirectional associations may not affect them. Furthermore, we found the heterogeneity in the UGC-park use link by UGC and urban park types. The geotagged UGC had a larger effect size on park use than the keyword UGC. Visits to comprehensive parks were significantly affected by UGC, while visits to community parks were not. This study sheds new light on increasing park use from the perspective of digital information, which benefits future research and policy development in modern society.

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Data Availability Statement included at the end of the article

Keywords
Urban park, park use, social media, user-generated content

Highlights

1. UGC quantity, rating, sentiment, and exposure were associated with park use.
2. UGC rating, sentiment, and exposure may significantly affect park use.
3. The geotagged UGC had a stronger effect on park use than the keyword UGC.
4. UGC had significant effects on the use of comprehensive parks but not on community parks.

Introduction

The usage of urban parks and exposure to greenery boost human well-being in multiple aspects, which include physical, mental, and social health (Twohig-Bennett and Jones, 2018). Understanding why some parks are more popular could inspire the planning and operation of urban parks to maximize the parks' benefits to urban residents (Chen et al., 2018; Rigolon and Németh, 2018; Song et al., 2022).

Considerable studies have examined the impacts of various physical and social factors on park use, including park attributes, accessibility, and features of surrounding area (Donahue et al., 2018; Guo et al., 2019; Hamstead et al., 2018; Zhang and Zhou, 2018). Park attributes, such as size, shape, service and facilities, and tree and water coverage, are critical in determining whether citizens will visit (Chen et al., 2018; Lyu and Zhang, 2019; Veitch et al., 2022). Moreover, park use is positively associated with park accessibility, often operationalized by street densities, the amount of adjacent public transit stops, distance to the urban center, or the quantity of transport service (e.g., parking lots) (Chen et al., 2018; Zhang and Zhou, 2018). The proximity, often measured by metric or topological distance, was also used to assess park accessibility. Besides, the social and physical features of the surrounding area have varying effects on how and how much citizens use them, including population density (Donahue et al., 2018; Li et al., 2020), socioeconomic status (Gu et al., 2020; Wang et al., 2021), development density, available facilities and services, and land-use mix (Donahue et al., 2018; Li et al., 2020; Lyu and Zhang, 2019; Zhang and Zhou, 2018; Zhou et al., 2021).

In addition to the aforementioned physical and social factors, user-generated content (UGC), as one crucial type of digital information, may potentially emerge as a pivotal factor influencing park use. The development of information communication technology and social media platforms has accelerated the accessibility and efficiency of digital information. Over four billion social media users worldwide browse and/or generate UGC on social media platforms, with Chinese users constituting roughly one-quarter (1.02 billion) in 2022 (Statista, 2022). UGC has affected many aspects of our everyday lives, including decision-making and social interaction (Bak-Coleman et al., 2021; Castells, 2011). Through UGC, former users can create their UGC to share information, personal experiences, and emotions through texts, photos, and videos (Liu et al., 2019; Xiang and Gretzel, 2010), while other users can access these UGCs or potentially affected by the UGC (Pop et al., 2021). Hence, UGC can be considered as a medium for spreading electronic word-of-mouth (e-WOM) about parks (Chen et al., 2014), which may have a crucial influence on park visitors' perceptions, actions, and expectations (Liu et al., 2019).

Although several studies have revealed a high correlation between UGC quantity and park use in recent years (Chen et al., 2018; Donahue et al., 2018; Hamstead et al., 2018; Li et al., 2020; Lyu and Zhang, 2019; Zhang and Zhou, 2018), they have not explored the potential impact of UGC quantity or other attributes of UGC (e.g., rating, sentiment, and exposure) on park use. They typically leverage abundant and readily accessible geotagged UGC data and employ UGC quantity as a proxy for park use to investigate the spatiotemporal distribution of park visitation at different spatial scales, such as city-wide (Zhang and Zhou, 2018) or national levels (Li et al., 2020). The lack of knowledge on the impact of UGC on park use may result in an insufficient understanding of how to boost park use in modern society.

Therefore, this study explored the effect of UGC on park use based on 613,858 park-related UGC and 251 urban parks in China. Our research extends existing studies in several aspects. First, this is among the first studies to explore the effect of UGC on park use. It enriched the theoretical framework of urban park use, highlighting UGC as a significant and non-negligible factor in modern society. Second, this study distinguished three distinct relationships between UGC variables and park use (Figure 1): UGC quantity may have a bidirectional association with park use; UGC rating/sentiment and park use may be affected by confounders of park attributes, accessibility, and features of surrounding area; UGC exposure may not be affected by bidirectional association or confounders. It proposed that using UGC rating, sentiment, and exposure to assess the effect of UGC on park use yields more robust results than UGC quantity because they may not be affected by bidirectional effects. Third, this study examined the heterogeneity of different UGC types and urban park types, thereby providing more specific support and design strategies for urban park design and management.

Related work and hypothesis

Existing greenspace studies related to UGC

User-generated content (UGC) describes media content that is created by the public and shared primarily online (Kaplan and Haenlein, 2010). In recent years, UGC on social media has been commonly used to support research on urban parks and greenspaces, which can be divided into two categories (Wilkins et al., 2021).

First, because there is a high correlation between the quantity of geotagged UGC and actual park use, the quantity of geotagged UGC has been used to assess park use, uncover park visiting patterns, and determine a park's hotspots and coldspots (Donahue et al., 2018; Hamstead et al., 2018).

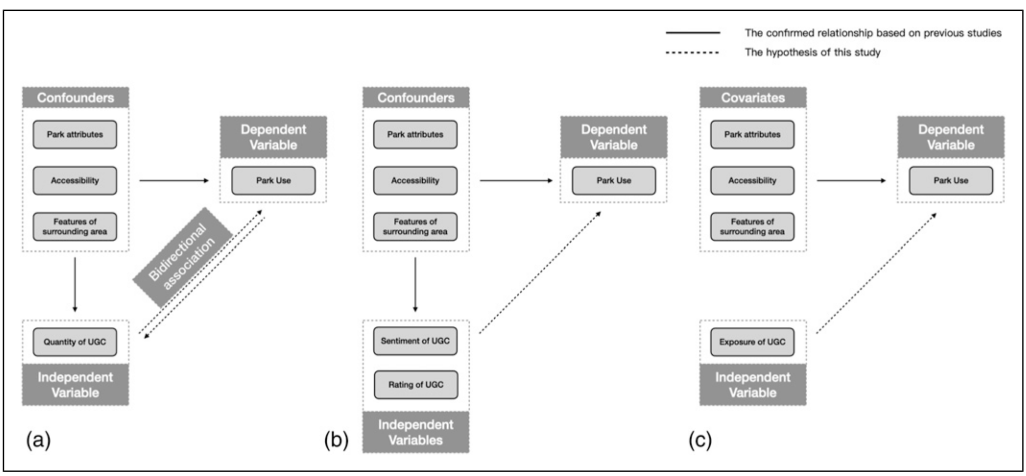

Figure 1. Three types of potential associations between UGC variables and park use. (a) The quantity of UGC and park use. There may be a bidirectional association between the quantity of UGC and park use. (b) The sentiment and rating of UGC and park use. The association between sentiment/rating of UGC and park use may be affected by confounders. (c) UGC exposure and park use. The factors affecting UGC exposure are exogenous factors; the association between UGC exposure and park use may not be affected by bidirectional associations and confounders.

Second, the experience of park visitors has been evaluated through the analysis of text, photos, and videos of UGC. Here, UGC has explicitly been used to reveal the sentiment of visitors (Cheng et al., 2021), for example, the preferred visiting locations and times and their feedback on locales, services, and the environment (Cord et al., 2015).

Although UGC has been widely employed to support park-related research, limited studies have examined the independent impact of UGC, which is prevalent in modern society, on park use itself.

UGC may influence park use

User-generated content may influence park use in the following ways. First, UGC may affect the park-use decision of prospective visitors when facing multiple choices. It has been considered a trustworthy source for decision-making, especially for multiple-choice comparisons (e.g., hotels, restaurants, and vacation locations) (Narangajavana Kaosiri et al., 2019; Tsiakali, 2018; Zhang et al., 2021). Second, positive UGCs may entice people who do not typically visit parks to become park visitors. Exposure to park-related UGC may subconsciously affect people with its captivating visuals and positive experiences (Liu et al., 2019; Narangajavana Kaosiri et al., 2019). This exposure may shape individuals' inclination to visit and expectations of parks, which, in turn, can result in an increase in park use.

In detail, characteristics of UGC, including quantity, rating, sentiment, and exposure, have varying effects on individuals' attitudes, actions, and expectations (Liu et al., 2019; Narangajavana Kaosiri et al., 2019; Zhang et al., 2021). The number of UGC has a positive impact on decision-making, but the greater the quantity of reviews, the smaller the increase in the effect on users' decision-making (Viglia et al., 2016). When comparing multiple possible options, UGC rating is the most visual representation of e-WOM and is the most efficient factor (Kim and Park, 2017; Viglia et al., 2016). Compared with UGC ratings, UGC content can communicate more intricate details, such as visitors' attitudes and the reasons for recommendations. Thus, UGC sentiment has also been identified as a crucial factor influencing people's decision-making (Lian and Yu, 2019; Mirzaalian and Halpenny, 2021). Moreover, social media influencers with high UGC exposure have been shown to significantly influence followers' attitudes (Pop et al., 2021) and improve their perceptions of specific destinations (Xu and Pratt, 2018).

Three types of associations between UGC variables and park use

Based on the literature review, we hypothesized that UGC quantity, rating, sentiment, and exposure would be associated with park use. However, as seen in Figure 1, there may exist three distinct relationships.

In the left model (Figure 1(a)), the association between park use and quantity of UGC may be the bidirectional association (i.e., more UGC leads to higher park use and vice versa) (Xu et al., 2021). If we assume an equal proportion of park visitors (say 1 out 100) would post UGC on their social media platforms, parks with more visitors would have a larger quantity of UGC. It is also feasible that the quantity of UGC may affect park use. Potential visitors may select to visit parks that are popular with higher UGC quantity (Xu et al., 2021). Hence, even if we observe a positive association between park use and the quantity of UGC, it is difficult to infer the effect of UGC quantity on park use (Spector, 2019; Wooldridge, 2015).

In the middle model (Figure 1(b)), we tentatively have not identified any bidirectional association that could affect UGC rating/sentiment and park use. However, previous studies showed that the potential confounders might influence both UGC rating/sentiment and park use. For instance, parks with adequate recreational facilities and good park attributes may lead to higher park use. At the same time, these positive features (e.g., green and water coverage) also lead to positive attitudes and preferences by park users (Cheng et al., 2021; Kong et al., 2022), thus reflected in park user's high ratings and sentiments in the UGC. Hence, the associations between park use and UGC can be attributed to the underlying confounders affecting both park use and UGC rather than the true effect of UGC on park use (Imbens and Rubin, 2015; Spector, 2019). Therefore, it is necessary to control for these confounders before inferring the effect of UGC rating/sentiment on park use.

In the right model (Figure 1(c)), the UGC exposure (i.e., the average view number of UGC) is not likely to be influenced by confounders in the previous models. Compared to the built environment, UGC exposure is more influenced by the exogenous factors, including the social popularity of users posting UGC, the quality of UGC content, and the features of social media platforms (Nguyen and Tong, 2022; Pop et al., 2021). It is plausible that at least some, if not the majority of, people who read the park-related UGC may be affected by the UGC. A park with a higher UGC readership online indicates more people read the park-related UGC, which in turn convinces some UGC readers to visit this park. Therefore, the observed associations between UGC exposure and park use are more likely to be explained by the effect of UGC on park use.

Methods

Study design

Guangzhou and Shenzhen in Guangdong Province were chosen as the study cities, which are two of the most developed cities in China and have similar locations, weather conditions, and cultural contexts. In the seventh national census in 2020, the populations of Guangzhou and Shenzhen were 18.67 million and 17.56 million, respectively. The weather of these cities is generally pleasant and conducive to outdoor activities on most days of the year.

We focus on the 251 urban parks in Guangzhou and Shenzhen. These parks have been accessible to the public for a minimum of 1 year, and their geographical boundaries can be obtained through the Baidu Maps Application Programming Interface (API). The Google Earth images were used to further calibrate the accuracy of the geographical boundary data. Based on the standard provided by the Ministry of Housing and Urban-Rural Development in China (Ministry of Housing and Urban-Rural Development of the People's Republic of China, 2017), parks are classified as community and comprehensive parks. These two types, as the standard points out, offer distinct amenities and cater to different citizens. Community parks (1–10 ha) are mostly small-scale urban green spaces that service nearby residents; comprehensive parks (>10 ha) offer comprehensive recreational amenities and developed infrastructure for sightseeing, resting, and cultural and sports activities, as well as provide a wide variety of services to visitors throughout a city. The selected urban parks are shown in Figure S1 (Supplementary Material 1).

For accurate modeling to examine the potential effect of UGC on park use, temporal precedence was considered during the data collection period (Imbens and Rubin, 2015; Spector, 2019). The park-use data were collected from November 27 to November 30, 2021 (Saturday to Tuesday), when the weather was warm and there was no precipitation. Moreover, during that time, the two cities did not implement any social distancing orders in the context of the COVID-19 pandemic. The UGC data collection period was between November 13 and November 26, 2021 (prior to park-use data). During this period, all park-related UGC data that the public can read on the platforms were collected. The other factors that may affect park use were selected based on the literature review, and they were collected in 2020 or 2021 (Supplementary Material 1, Table S1).

Variables

Urban park use. In this study, Baidu Heatmap was selected to compute the number of human activities in parks to quantify park use, which has been widely used as a proxy (e.g., for park use or population distribution) and has been confirmed to constitute accurate and trustworthy datasets in several urban studies (Fan et al., 2021; Li et al., 2019, 2021; Lyu and Zhang, 2019). In China, Baidu is the most popular search engine and website and has a daily response volume of 6 billion (Li et al., 2019). In 2011, Baidu created Baidu Heatmap as a big data tool to depict the real-time spatial distribution of all Baidu users (who use Baidu's applications, e.g., Baidu Search and Baidu Maps).

Considering the previous experimental design for Baidu Heatmap data, we chose the period from November 27, 2021, to November 30, 2021 (Saturday to Tuesday). During the data collection, the heat map data were collected every 2 h (from 07:00 to 21:00) for each of the selected urban parks. We obtained 32 heat maps with a 1-m spatial resolution. Each pixel of the heat maps evaluated the relative number of people (Lyu and Zhang, 2019). Then, the heat map data were overlaid on the park boundaries; the raster calculator in ArcGIS Pro 2.9.1 was employed to calculate park use. Finally, the relative number of people visiting each park was measured every 2 h. The average value of 32 heat maps for each park was used as the dependent variable for this study.

UGC variables. The UGC on five popular social media platforms in China (Sina Weibo, Ctrip, DaZhong DianPing (DZDP), TikTok, and Kuaishou) was selected as the dataset in this study. Among these social media platforms, the UGC on Sina Weibo, Ctrip, and DZDP include a "check-in" or geotagging feature. The geotagged UGC (i.e., posts with check-in features) consists of user-initiated uploads of a geographic location, for example, a park or a building (Li et al., 2020; Zhang and Zhou, 2018). In addition, we collected the keyword UGC from Weibo, TikTok, and Kuaishou, which do not contain any geographic location and are generally available to users through keyword searches or push notifications from mobile apps. Six sets of UGC were gathered and divided into geotagged UGC and keyword UGC (Supplementary Material 1, Figure S2).

The Scrapy package in Python 3.7 was employed to crawl the UGC, which can better simulate how people browse social media via their web browsers or apps. The geotagged UGC was collected through the check-in pages of various urban parks, while the keyword UGC was collected through a keyword search based on the city and park names. Data were collected in full compliance with strict privacy and data security regulations. A total of 613,858 UGC presented on the platforms from November 13 to 26, 2021, were obtained (before the collection time of park-use data). This study involved a four-step process for cleaning UGC data, which included (1) the removal of UGC that only contains punctuation, URLs, numbers, symbols, and non-Chinese letters; (2) the elimination of URLs, symbols, and non-Chinese characters from the leftover UGC; (3) the exclusion of UGC with fewer than two Chinese symbols to minimize the possibility of incorrect sentiment classification; (4) removing UGC that was unrelated to parks manually. Lastly, 346,286 UGC were retained for the study (Figure S2).

User-generated content quantity, rating, sentiment, and exposure were calculated by the Python Pandas package based on their metadata. We calculated the number of UGC for different platforms to evaluate the UGC quantity. The UGC rating (only available for DZDP and Ctrip) was calculated based on the average rating of park-related UGC. The UGC sentiment was calculated with the Baidu Natural Language Processing Platform (https://ai.baidu.com/easydl/nlp). The accuracy of this platform for examining users' sentiment in Chinese social media UGC has been verified and utilized in recent park-related studies (Cheng et al., 2021; Kong et al., 2022). The sentiment scores range from 0 to 2 (with 0 indicating "very negative sentiment" and 2 indicating "extremely favorable sentiment"). We evaluated the UGC sentiment of each park via the average UGC sentiment value. UGC exposure (not available for DZDP and Ctrip) was calculated through the average view number of park-related UGC.

Other factors affecting park use. The other factors, including park attributes, accessibility, and features of surrounding area, were assessed based on multi-source big data, respectively. In detail, park attributes included five controlled variables: park area, landscape shape index (LSI), normalized difference water index (NDWI), normalized difference vegetation index (NDVI), and park facility quantity. Accessibility consisted of six controlled variables: road density, public transit density, transportation service density around the park, the distance between the park and the urban center, closeness, and betweenness. Features of surrounding area comprised seven variables: building coverage, mean height of building, service facility density, POI richness, POI entropy, socioeconomic status (SES), and population density. The detail of variable calculation is present in Supplementary Material 1.

Statistical analysis

First, a correlation matrix was calculated to explore the relationship between the quantity, rating, sentiment, and exposure of UGC. The unpaired *t* test was then employed to examine the differences between the different variables of comprehensive and community parks.

After that, the regression models were used to examine the association between UGC and park use. The potential multicollinearity was considered among the independent variables. Factors with VIF ≥4 were removed from the models (O'brien, 2007). The natural logarithm of the value of park use was taken to ensure that the data conformed to a normal distribution. To examine the standardized coefficient, all variables were centered at their mean and scaled by their standard deviation (SD). The coefficients of UGC variables for park use are interpreted as changes in logged park-use value per one SD change of UGC variables. To consider the spatial effects to avoid bias, we developed pre-tests for our model. The results of Moran's I ($p > .05$) for the independent and dependent variables, as well as the Lagrange multiplier pre-tests ($p > .05$) for the model, showed that no significant spatial correlation was found in this study (Anselin et al., 2010). Therefore, hierarchical linear regression was employed to evaluate the standardized effect of UGC factors on park use by controlling for various factors.

In detail, Model 1 includes the attributes of parks, accessibility, and the features of the surrounding area. It served as a baseline model, so we could compare the effect of UGC variables and that of other park-use factors confirmed in previous studies. In addition to all the variables in Model 1, Models 2 to 5 contain the geotagged and keyword UGC variables: quantity, rating, sentiment, and exposure, respectively. The hierarchical nature of the models (Models 2 to 5 vs Model 1) allowed us to uncover the effect of different aspects of UGC on park use.

Moreover, the two types of parks provide a variety of amenities and are attractive to various types of visitors. Thus, the data were further split into comprehensive and community parks to clarify the key variables that drive different types of visitors to the two types of parks. A separate hierarchical linear regression was used for both types of parks. The VIF values of all models are shown in Table S2 (Supplementary Material 2). According to the Shapiro–Wilk test ($p > .05$), the residuals in all models were normally distributed. In addition, the residuals were not found to have spatial autocorrelations (Moran's I test, $p > .05$).

All data analyses were carried out in GeoDa and R v4.0.2 with the "lmer" package (R Core Team, 2020). The adjusted R^2, standardized coefficient, and p-values were reported.

Results

Characteristics of UGC, park use, and other factors

The attributes of UGC were illustrated in Figures S3 and S4 (Supplementary Material 2). The distribution of park data across the six groups of UGC was uneven. There were 124 parks with UGC on all social media platforms, while only 2 parks with no UGC on any platform. The number of UGC related to the sampled parks on different social media platforms differed widely, ranging from 4,056 to 167,504 (Figure S4a). Moreover, the distribution of UGC across different types of parks varied greatly. There were 5 parks with more than 10,000 posts and 16 parks with fewer than 10 posts. Although some sample parks had less UGC, these UGC sentiments, ratings, and exposure could still potentially influence human behavior, as demonstrated in previous studies (Liu et al., 2019; Pop et al., 2021). Thus, we used all samples, rather than excluding samples with less UGC, for further analysis.

Figure S4b showed that the comprehensive parks had higher UGC numbers (M = 2295.0, SD = 3166.0) than the community parks (M = 371.6, SD = 617.4). The unpaired *t* test showed that the difference in the number of UGC related to comprehensive parks and community parks was significant ($p < .001$).

Table S1 showed the correlation matrix of UGC attributes. High correlations were found between UGC sentiment and rating. UGC quantity was moderately associated with UGC rating and sentiment. However, UGC exposure was not significantly associated with UGC quantity, rating, and sentiment. Figure S5 (Supplementary Material 2) illustrated the spatial distribution of UGC attributes. The sentiment and rating of UGC had a similar distribution, while the spatial distribution of UGC exposure seemed different from the UGC quantity, rating, and sentiment.

The geographic mapping of urban park use was shown in Figure S6 in Supplementary Material 2. Tables S3–S5 illustrated the features of all sampled parks, whether comprehensive or community parks. The unpaired two-sample *t* test (Table S3) revealed that data about comprehensive and community parks had significant differences.

The effect of UGC on urban park use

We used hierarchical linear regression to estimate the associations among park use, UGC, and other factors for all parks, comprehensive parks, and community parks (Table 1).

For all parks, Model 1a showed that the combination of park attributes, accessibility, and the features of the surrounding area was significantly relevant to park use (adjusted R^2 of 0.762, $p <$ .001). The UGC factors, including the quantity, rating, sentiment, and exposure, were added to Models 2a to 5a, respectively. The overall explanatory power of Models 2a to 5a increased significantly compared to that of Model 1a ($p < .001$). The results showed that the quantity, rating, sentiment, and exposure had significant associations with park use after controlling for the other factors. Most geotagged UGC variables (6 out 8) had significant and positive effects on park use. Only one keyword UGC variable (1 out 8) was significantly related to park use (Figure 2(a)).

The results of comprehensive parks were in line with those of all parks. The results showed that the quantity, rating, sentiment, and exposure were significantly associated with comprehensive park use. All geotagged UGC variables were significant, while none of the keyword UGC variables were in Model b (Figure 2(b)).

The results for community parks differed from those of comprehensive and all parks. After adding UGC variables, Models 2c to 5c revealed no significant increase in explanatory power compared with Model 1c. The results indicated that the UGC had no significant impact on community park use (Figure 2(c)).

Discussion

The effects of UGC on park use

In our study, quantity, rating, sentiment, and exposure of UGC were all positively associated with park use. However, the level of confidence in inferring the effect differs among the three types of UGC variables. As described in the section of "Three types of associations between UGC variables and park use", a park visited more often is more likely to be posted UGC by park users, while a higher UGC quantity may attract more park visitors. Thus, although the positive association between geotagged UGC quantity and park use (coefficient of GeotaggedQuantity

Table 1. The results of hierarchical linear regressions.

	All parks (N = 251)					Comprehensive parks (N = 123)					Community parks (N = 128)				
	Model 1a	Model 2a	Model 3a	Model 4a	Model 5a	Model 1b	Model 2b	Model 3b	Model 4b	Model 5b	Model 1c	Model 2c	Model 3c	Model 4c	Model 5c
Model predictors	Standardized coefficient (β)														
Park attributes															
ParkArea	0.238***	0.228***	0.253***	0.248***	0.243***	0.489***	0.448***	0.477***	0.493***	0.465***	0.792***	0.810***	0.765***	0.741***	0.788***
LSI	−0.195***	−0.155***	−0.138***	−0.128***	−0.182***	−0.175**	−0.132*	−0.160**	−0.108	−0.145*	−0.016	−0.027	−0.016	−0.008	−0.017
NDWI	0.233***	0.198***	0.176***	0.188***	0.224***	0.239***	0.238***	0.222***	0.249***	0.256***	−0.055	−0.069	−0.069	−0.054	−0.056
NDVI	0.409***	0.371***	0.320***	0.296***	0.400***	0.285***	0.277***	0.252***	0.234**	0.336***	0.095*	0.104*	0.106*	0.082*	0.095*
ParkFacility	0.227***	0.147**	0.156***	0.161***	0.198***	0.224***	0.169*	0.179**	0.170**	0.205***	0.076	0.077	0.077	0.070	0.067
Accessibility															
RoadDensity	0.025	0.003	0.002	−0.039	0.029	0.002	−0.045	−0.059	−0.058	−0.030	−0.016	−0.031	−0.023	−0.041	−0.014
PublicTransitDensity	0.021	0.006	0.013	0.020	−0.006	−0.050	−0.102	−0.007	0.012	−0.078	−0.017	−0.029	−0.010	−0.017	−0.019
TransportationService	0.128**	0.130**	0.092*	0.140***	0.123**	0.188*	0.229**	0.211**	0.313***	0.201*	0.064	0.107	0.033	0.047	0.035
DistanceCenter	0.102*	0.106**	0.091*	0.089*	0.099*	0.077	0.077	0.073	0.070	0.082	−0.026	−0.025	−0.015	−0.017	−0.019
Closeness	0.058	0.066	0.073*	0.051	0.059	0.020	0.023	0.050	0.053	−0.015	−0.037	−0.037	−0.049	−0.046	−0.034
Betweenness	0.040	0.021	0.011	0.017	0.031	0.030	0.043	0.008	0.001	0.044	0.060	0.075	0.044	0.040	0.067
Features of surrounding area															
BuildCoverage	−0.066	−0.037	−0.039	−0.013	−0.062	0.021	0.040	0.027	0.065	0.055	−0.115*	−0.103	−0.120*	−0.095*	−0.116*
MeanHeight	0.031	0.024	0.046	−0.009	0.022	−0.028	−0.040	0.004	−0.023	−0.075	−0.049	−0.066	−0.046	−0.092	−0.051
ServiceFacility	−0.181***	−0.202***	−0.167***	−0.209***	−0.173**	−0.183	−0.209	−0.258*	−0.342**	−0.184	0.056	0.071	0.064	0.034	0.049
Richness	0.046	0.070	0.049	0.069*	0.066	0.081	0.073	0.059	0.122	0.105	0.039	0.047	0.059	0.063	0.041
Entropy	0.006	−0.004	−0.002	0.016	0.006	0.051	0.065	0.045	0.105	0.064	0.022	0.010	0.027	0.011	0.003
SES	0.072	0.030	0.011	0.054	0.061	0.039	−0.051	−0.005	0.018	0.012	−0.001	−0.003	0.003	0.021	0.006
PopulationDensity	0.012	−0.003	0.010	0.013	0.015	−0.089	−0.081	−0.040	−0.041	−0.092	0.041	0.039	0.047	0.062	0.055
User−generated content															
GeotaggedQuantity (Sina Weibo)		0.231***					0.238***					0.095			
GeotaggedQuantity (Ctrip)		0.024					−0.049					−0.091			
KeywordQuantity (Sina Weibo)		−0.040					−0.032					0.120			
KeywordQuantity (TikTok)		0.061					−0.039					−0.079			
GeotaggedRating (Ctrip)			0.120***					0.166**					−0.070		
GeotaggedRating (DZDP)			0.230***					0.236***					0.096		
GeotaggedSentiment (Sina Weibo)				0.163***					0.127*					0.086	
GeotaggedSentiment (Ctrip)				0.164***					0.187**					−0.039	
GeotaggedSentiment (DZDP)				−0.031					−0.070					0.009	
KeywordSentiment (Sina Weibo)				0.041					0.041					0.032	
KeywordSentiment (Kuaishou)				0.061					−0.080					0.068	
KeywordSentiment (TikTok)				0.031					0.083					0.010	
GeotaggedExposure (Sina Weibo)					0.098**					0.085*					0.016
KeywordExposure (Sina Weibo)					0.001					0.090					0.030
KeywordExposure (Kuaishou)					0.070*					−0.030					0.053
KeywordExposure (TikTok)					−0.005					0.005					−0.013
Adjusted R^2	0.762***	0.793***	0.817***	0.826***	0.772***	0.713***	0.747***	0.740***	0.757***	0.723***	0.705***	0.711***	0.712***	0.715***	0.703***
ANOVA Chi-sq of R^2 change		40.729*** (vs.Model 1a)	68.501*** (vs.Model 1a)	84.749*** (vs.Model 1a)	13.715** (vs.Model 1a)		22.47*** (vs.Model 1b)	14.26*** (vs.Model 1b)	26.731*** (vs.Model 1b)	8.726* (vs.Model 1b)		8.890 (vs.Model 1c)	4.769 (vs.Model 1c)	9.982 (vs.Model 1c)	2.364 (vs.Model 1c)

Note: * indicates $p < .05$, ** indicates $p < .01$, and *** indicates $p < .001$.

[Sina Weibo] = 0.231, $p < .001$) aligns with prior research (Donahue et al., 2018; Hamstead et al., 2018; Li et al., 2020), the reverse effect or bidirectional effect prevents our ability to infer the effect of UGC on park use.

Compared with UGC quantity, the results for UGC rating, sentiment, and exposure are more robust because they may not be affected by bidirectional associations. Hence, after controlling for confounders in the models, we can infer relatively compelling effects of UGC ratings, sentiment, and exposure on park use.

According to the model results (Model a), the inclusion of UGC variables led to a significant enhancement in the model's explanatory power ($p < .001$), and the variables of UGC rating, sentiment, and exposure showed statistical significance. Notably, UGC rating (DZDP) demonstrated a high standardized coefficient (0.230, $p < .001$), just lower than NDVI and park area, ranking as the third-highest coefficient in the entire model. The coefficients for significant UGC sentiment and exposure variables ranged from 0.163 to 0.164 and 0.070 to 0.098, respectively.

The results indicated that UGC may have positive effects on park use (Imbens and Rubin, 2015; Spector, 2019). Furthermore, the coefficients of the significant UGC variables were comparable to those of other physical and social variables, which is in line with our hypothesis. The constant involvement of digital information in our everyday lives challenges the notion that physical and social attributes (e.g., park features and accessibility) are the exclusive determining factors (Batty, 2013). Instead, digital information (e.g., UGC) may also independently influence urban park use.

We provide two tentative mechanisms that explain the link between UGC and park use. First, some potential park users may seek information online to decide which park to visit prior to actual park visitation. Thus, a park with a high UGC rating and sentiment is more likely to affect their decision-making in selecting a park. This is consistent with other research findings based on surveys that social media affects people's decision-making (e.g., selection of hotel, restaurant, and vacation location) (Jacobsen and Munar, 2012; Narangajavana Kaosiri et al., 2019; Pop et al., 2021; Tsiakali, 2018; Zhang et al., 2021). Second, higher UGC exposure may attract more non-park visitors to become park visitors. Exposure of park-related UGC can have a subconscious influence on individuals via its eye-catching visuals and memorable experiences (Liu et al., 2019; Narangajavana Kaosiri et al., 2019). As a result, parks with higher UGC exposure may attract more visitors who are not regular park-goers, leading to higher park use among these parks.

The heterogeneity of UGC and urban park

In our results, there existed heterogeneity in the effects of different UGC types on park use, as well as the effects of UGC on different park categories (Figure 2).

First, nearly all geotagged UGC variables exhibited significant positive effects on park use, whereas only a few keyword UGC variables demonstrated statistical significance. This may be because geotagged UGC requires geographic tags and needs to be posted inside the park or within a specific distance of the park, but there are no restrictions about where keyword UGC is made. Thus, compared to the keyword UGC, the vast majority of geotagged UGCs were more related to the parks and contained more detailed experiences or sentiments of previous users (Donahue et al., 2018; Zhang and Zhou, 2018). This is consistent with previous studies that more detailed and reasonable UGC may have a stronger influence on travel decisions (Lian and Yu, 2019). In addition, we observed distinct effects of UGC from various social media platforms, possibly due to differences in user numbers, age distribution, geographic presence, and other platform-specific factors (Statista, 2023).

Second, UGC was significantly associated with comprehensive park use but not community park use. We postulated that the results may be attributed to the varying magnitudes of park-related UGC variables and varying intentions of residents to visit different types of parks. In

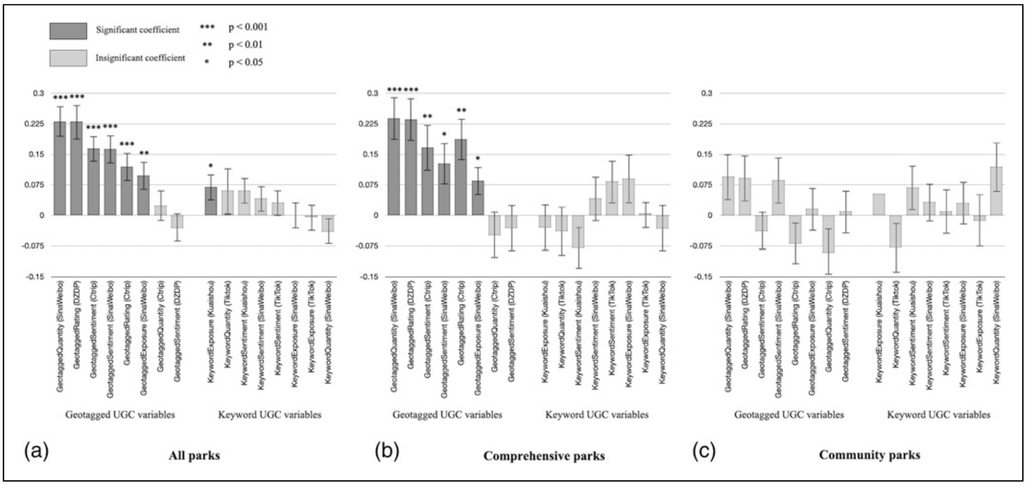

Figure 2. Standardized coefficients and 95% CIs of geotagged and keyword UGC variables. (a) The coefficients of all parks; (b) the coefficients of comprehensive parks; (c) the coefficients of community parks.

detail, the values of UGC variables related to comprehensive parks were nearly all significantly higher than those related to community parks (Table S3). This indicated that comprehensive parks have a greater quantity of UGC, featuring more positive sentiment and achieving higher exposure. Consequently, compared to community parks, the UGC related to comprehensive parks may be more attractive to visitors. Moreover, visitors to comprehensive parks are usually far from home (Cheng et al., 2021) and may be less familiar with these parks. These visitors typically have higher expectations or specific goals for their visit (e.g., hiking a particular trail and seeing a specific landmark) (Tieskens et al., 2018). Thus, these visitors may rely more on UGC as it provides more in-depth and valuable insights into the park's amenities, accessibility, and overall experience (Narangajavana Kaosiri et al., 2019; Zhang et al., 2021), helping visitors to better plan their trip. In contrast, community parks are generally located within walking distance of park users' homes. People typically visit community parks for everyday exercise or social connections, which may be less impacted by UGC.

Implication

The findings of this work theoretically and practically contribute to future research, policy development, and management. First, this study showed that except for the physical built environment and social variables previous studies have been discussing, the UGC, one crucial type of digital information, may affect park use. It provides a new theoretical perspective for understanding the factors that affect park use in modern society. We recommend that geotagged UGC be seen as a catalyst to promote park use, especially for comprehensive parks. Park managers should promote parks via UGC and encourage visitors to post more during their visits, which may increase UGC exposure and attract more visitors. It is also recommended that park managers monitor reviews and ratings on UGC platforms, particularly negative and low-rating UGC. Responding to negative feedback in a timely manner and providing clarifications can help mitigate the negative consequences of park use from these reviews. Second, we found that UGC rating, sentiment, and exposure may be reliable variables to estimate the effect of UGC on park use. This provides valuable insights for future research on the effects of UGC.

Limitations

Although our findings shed light on the understanding of the potential impact of UGC on park use, this cross-sectional study still has many inherent limitations. We point out several directions for further studies.

First, our findings are limited to the population of heavy mobile phone users and may not be applicable to the general population. We employed Baidu Heatmap data as a proxy to evaluate park use. Although it provides better spatial coverage than traditional methods (e.g., social surveys or site observation), this location-based service dataset can only measure park use among heavy mobile phone users. This limitation may lead us to overlook individuals with light smartphone usage (e.g., seniors and middle-agers), who are also essential user groups for park use in China. Furthermore, considering the quantity of social media users significantly across different age groups (Liu et al., 2019), the effects of UGC on demographics like seniors and middle-agers may differ significantly from those highly dependent on smartphone usage (e.g., younger adults). Therefore, we recommended that future research adopt survey-based methods to comprehensively examine the effect of UGC on the entire population and different demographic segments. This approach would facilitate a more detailed analysis of the heterogeneity in UGC effects on different age groups.

Second, our sample parks were only from first-tier cities in China; the generalizability of our findings to all cities requires further validation. Existing research on park use and its influencing physical and social variables has identified significant differences among different cities due to varying infrastructure, population, and economic factors (Li et al., 2020). We speculated that UGC effects may vary across cities due to differences in the development of digital infrastructure and smartphone penetration rates across different city tiers. Hence, future research should acquire larger-scale data (e.g., regional or national level) for conducting multi-city comparisons to examine this topic.

Third, this study is subject to the limitations of a cross-sectional study design. It was unable to uncover the long-term dynamics of UGC variables and park use, as well as examine the causal relationship between UGC and park use. Future research needs to use a longitudinal dataset combined with a quasi-experimental design to verify the causal relationship between UGC and park use.

Conclusion

This research is an initial attempt to explore the effect of UGC on urban park use. After controlling for park attributes, accessibility, and the features of the surrounding area, we found that the quantity, rating, sentiment, and exposure of UGC are significantly associated with urban park use. The observed associations among UGC rating, sentiment, exposure, and park use provide more solid evidence for the effect of UGC on park use. Geotagged UGC may have a stronger effect on park use than keyword UGC. UGC might significantly affect the use of comprehensive parks but not the use of community parks. The results of this study reveal that UGC may be an effective factor in increasing urban park use and thereby improving human well-being.

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Data availability statement

Datasets in the current study are available from the authors on reasonable request.

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Supplemental Material

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