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Deciphering the effect of user-generated content on park visitation: A comparative study of nine Chinese cities in the Pearl River Delta

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ABSTRACT

Identifying key factors affecting park visitation is critical for promoting park visitation and maximizing parks' health and social benefits. Little research has comprehensively revealed the effects of UGC on park visitation within a large regional context, despite its pervasive influence in modern society. Furthermore, although existing research indicated that factors influencing park visitation may vary across different cities, few studies have linked such heterogeneity to different city levels, i.e., cities with different economic status, population size and urbanization level. In this study, we performed comparative research to reveal the effect of UGC on park visitation in nine cities with different urban contexts and economic levels within the Pearl River Delta (PRD), China based on 1,771,093 UGC and mobility data of sample parks. Our results demonstrated that UGC exposure, sentiment, and rating had significant effects on park visitation across all PRD cities; the effect of UGC rating was higher than that of most other variables. Furthermore, most high-value clusters of UGC were concentrated in first-tier cities, while low-value clusters were in non-first-tier cities. Moreover, the effects of UGC variables showed a decreasing trend with lower city levels, while the effect of certain built environment variables exhibited an increasing trend with lower city levels. Our study sheds light on the key factors in park usage, providing effective pathways for policymakers and urban designers to maximize the utilization of urban parks across various city types in modern society.

1. Introduction

Urban parks are gaining research traction as they are increasingly recognized as having a positive impact on physical activity and health outcomes in urban environments (Markevych et al., 2017). They are frequently used as attractive locations for walking, jogging, and bicycling, especially for health and leisure purposes (Halkos et al., 2022; Jiang et al., 2022; Wei, Lu, et al., 2023). Utilizing urban parks and being around greenspaces boost human well-being, including physical, psychological, and social health (D. Liu, Jiang, et al., 2023; Markevych et al., 2017; Stępniewska, 2021). Therefore, determining why some parks are used more regularly or extensively than others would maximize the health, well-being, and sociability benefits of urban greenspaces (Jiang et al., 2021; Wu et al., 2020). The usage of urban parks is affected by a number of factors and complicated relationships. Existing research examined that park attributes, surrounding characteristics, and accessibility may influence park visitation (Fan et al., 2021; Guo et al., 2019).

Although various studies investigated the effects of the built environment variables on park visitation across large regional contexts, limited research has further delved into the association between user-generated content (UGC), which plays an essential role in the digital age, and park visitation within such expansive regions. Relying on information and communication technology (ICT), UGC has been an essential part of city residents' everyday lives (Castells, 2011; Cuomo et al., 2021); there were 926 million users who shared and read UGC on social media in China in 2020 (Statista, 2023). It has changed how city residents seek and disseminate information as well as interact with each other (Hughes et al., 2012). Via location-specific UGC, former visitors can share their experiences, while prospective visitors can gather

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information to select potential locations to visit. As a result, UGC can disseminate electronic word-of-mouth (e-WOM) as a medium, which operates asynchronously and potentially affects human behavior (Y.-C. Chen et al., 2014).

In addition, prior research was often performed in a single city since it was challenging to collect data across multiple cities simultaneously. It may pose a major research challenge to generalize the research findings since the affecting variables of park visitation often vary among different cities (Donahue et al., 2018; Lyu and Zhang, 2019). For example, park visitation in more developed cities (e.g., first-tier cities and municipalities) was significantly positively associated with public transit density but had no significant association with surrounding point of interest (POI) density (F. Li et al., 2020; S. Zhang and Zhou, 2018). Conversely, park visitation in relatively less developed cities (e.g., second or third-tier cities, prefecture-level cities) had a significant negative correlation with public transit density and a positive association with surrounding POI density (F. Li et al., 2020). Similar to the built environment variables influencing park visitation, research has also found variations in the spreading characteristics and effects of UGC because of differences in urban development, regional culture, or media environment (Gretzel et al., 2008; Zhang et al., 2021).

Although some research in recent years has confirmed a high correlation between UGC numbers and park visitation, their aim was to use UGC numbers as a proxy to examine the spatiotemporal distribution of park visitation (Wilkins et al., 2021). As far as we know, no study has comprehensively demonstrated the effects of UGC on park visitation across different urban contexts and economic levels. Insufficient investigation of the association between UGC and park visitation could result in overlooking the essential variables that may influence park visitation in modern society. Our research represents a preliminary examination to investigate the effects of UGC and establish corresponding associations.

2. Literature review

2.1. UGC may affect park visitation

UGC, which is a key characteristic of Web 2.0, refers to content publicly shared on online platforms. UGC is defined by three fundamental criteria: firstly, it must be disseminated on either a publicly accessible website or a social networking platform accessible to a specific audience; secondly, it must demonstrate a discernible level of creative input; and lastly, it should originate from non-professional routines and practices (Kaplan and Haenlein, 2010).

UGC may affect park visitation in two ways. First, because it is voluntarily and independently generated by previous visitors, UGC has been seen as a trustworthy source of information to make decisions, especially when comparing multiple choices of destinations (e.g., restaurants, hotels) (Tsiakali, 2018). Thus, the e-WOM of urban parks created by UGC may take a crucial role in the decision-making of prospective park visitors, thereby attracting more people to the park and increasing park visitation. Second, positive UGCs may stimulate citizens' willingness to visit parks. Be exposure to UGC, individuals can subconsciously be influenced by its content, such as stunning scenery and unforgettable moments (H. Liu et al., 2019). Such exposure has the potential to influence individuals' visiting intentions and expectations, ultimately increasing park use.

More specifically, the rating, sentiment, and exposure of UGC could influence individuals' intentions and motivation (H. Liu et al., 2019; Mirzaalian and Halpenny, 2021; Nisar and Prabhakar, 2018; Y. Zhang et al., 2021). UGC rating, which serves as a prominent visual manifestation of e-WOM, is a vital variable for individuals and the most graphic form of e-WOM when faced with multiple choices (Kim et al., 2017; Viglia et al., 2016). While it is difficult for individuals to get detailed views from ratings, UGC content can convey more details (e.g., the quality of the destination, visitor attitudes); its sentiment has been seen as a main factor affecting individuals' decision-making (Mirzaalian and Halpenny, 2021; Nisar and Prabhakar, 2018). Besides, negative emotions typically exert a more substantial effect on people's decision-making than positive emotions (Nisar and Prabhakar, 2018). Furthermore, existing research demonstrated that social media influencers with higher UGC exposure might affect followers' decision-making (Pop et al., 2021), especially increasing favorable attitudes toward destinations (Xu and Pratt, 2018).

2.2. Other influencing factors of park visitation

Existing research has investigated that factors including park attributes, characteristics of park surrounding environment, and park accessibility may influence park visitation (Fan et al., 2021; Guo et al., 2019). First, park attributes, such as area, greenery and water cover, recreational activities, and park form, are significantly associated with park visits (Y. Chen et al., 2018; Veitch et al., 2022). Second, the accessibility of a park assesses the relative ease by which urban residents can reach this park. The accessibility of a park is often measured by variables related to transportation infrastructures such as bus and metro stops, and road density (Fan et al., 2021; Lyu and Zhang, 2019), or topological or metric properties of a street network, e.g., distance from the city center, closeness, betweenness (Chiang and Li, 2019; Cooper, 2015). Third, a park surrounded by a well-designed environment is more likely to have high park usage. Building coverage, land use mix, services and amenities, the density of the surrounding population, and socioeconomic status (SES) have been significantly associated with park visitation (Guo et al., 2019; D. Liu et al., 2023; Xing et al., 2018).

Furthermore, park attributes, characteristics of the park surrounding environment, and park accessibility may also serve as confounders influencing both UGC and park visitation (Kong et al., 2022; Wei, Liu, et al., 2023). Hence, such confounders should be controlled when examining the effects of factors on park visitation (Imbens and Rubin, 2015; Wei, Wang, et al., 2023).

In detail, park attributes, especially greenery and water features, have a critical effect in increasing UGC rating and sentiment of park visitors through three pathways: mitigation, which entails decreasing the effect of a hostile environment (e.g., air pollution, urban heat island); restoration, which aids restoration of concentration and psychophysiological stress; and entertainment, which provides a venue for physical activity and socializing (Markevych et al., 2017). Thus, a well-designed urban park that offers abundant and varied greenspaces and water features may increase the mood and overall experience of its visitors, leading them to post UGC with positive ratings and sentiments (Kong et al., 2022; Wei et al., 2023). Moreover, positive correlations have been identified between the sentiment of park visitors and characteristics of the park surrounding environment. Individuals who reside in a well-built and high-SES environment could experience increased sentiment (Kong et al., 2022). As a result, these visitors could be more likely to post park-related UGC with higher sentiment values. In addition, research has demonstrated a positive association between park accessibility and visitors' sentiment (X. Zhu et al., 2021). Extended and uncomfortable travel could decrease satisfaction and heightened stress levels among visitors (J. Zhu and Fan, 2018). Thus, difficulties in accessing the park may have the potential to lower visitors' sentiment, leading to negative UGC sentiment and ratings.

2.3. Research gaps and our study

In summary, there is little research examining UGC's effects on park visitation within large regional contexts, even though UGC has been an essential part of everyday lives (Y.-C. Chen et al., 2014). In addition, despite studies pointing out that the effects of variables influencing park visitation may vary across different urban contexts (Donahue et al., 2018), no studies have assessed whether UGC variables have varying effects on park visitation across different city levels. To fill in the knowledge gaps, this study employed the multi-source geographic big data of 874 urban parks with 1,771,093 park-related UGC from nine cities with different city levels within one metropolitan area in China to investigate the association between park visitation and UGC.

Our research made two contributions to the existing literature. First, it stands among the pioneering efforts to comprehensively evaluate the effects of UGC on park visitation within a large regional context, enhancing the knowledge of the factors influencing park visitation in modern society. Second, it unveiled the potential spatial heterogeneity of UGC effects on park visitation across different city levels. This provides a quantitative assessment for the government to tailor their planning and management policies to different cities, thereby increasing greenspace exposure and fostering a more resilient and healthier urban environment.

3. Methods

3.1. Study design

All cities located at the Pearl River Delta (PRD) metropolitan area in Guangdong Province, China, were selected for this study (Fig. 1a and b). PRD is a pioneering region in China's economic reform, and it accounts for 79.7 % of the total economic output of Guangdong province (Guangdong Bureau of Statistics, 2022). It has developed into an important financial center in China. Based on the China City Classification List (China Business Network, 2019) and the Guangdong Statistics Website (Guangdong Bureau of Statistics, 2022), the nine cities within the PRD were classified into four tiers (Table 1).

Based on the application programming interface (API) provided by Baidu Map (https://lbsyun.baidu.com/), we collected vector data of 874 unique urban parks in nine cities, including their POI and the park boundary. The correctness of the spatial boundary was further validated using Google Earth images. These urban parks, which cover over 836 square kilometers, served as the sample to identify the variables that may affect park visitation, as shown in Fig. 1c and d.

The temporal order in data collection was carefully considered in this study. The period from November 27 through November 30 of the year 2021 (Saturday to Tuesday) was chosen to collect park use data for the parks, while the collection of UGC preceded the timeframe for park visitation data. We collected all UGC related to sample parks presented on the major Chinese social media platforms from November 13 to November 26, 2021. Besides, all data of controlling variables were collected between 2020 and 2021.

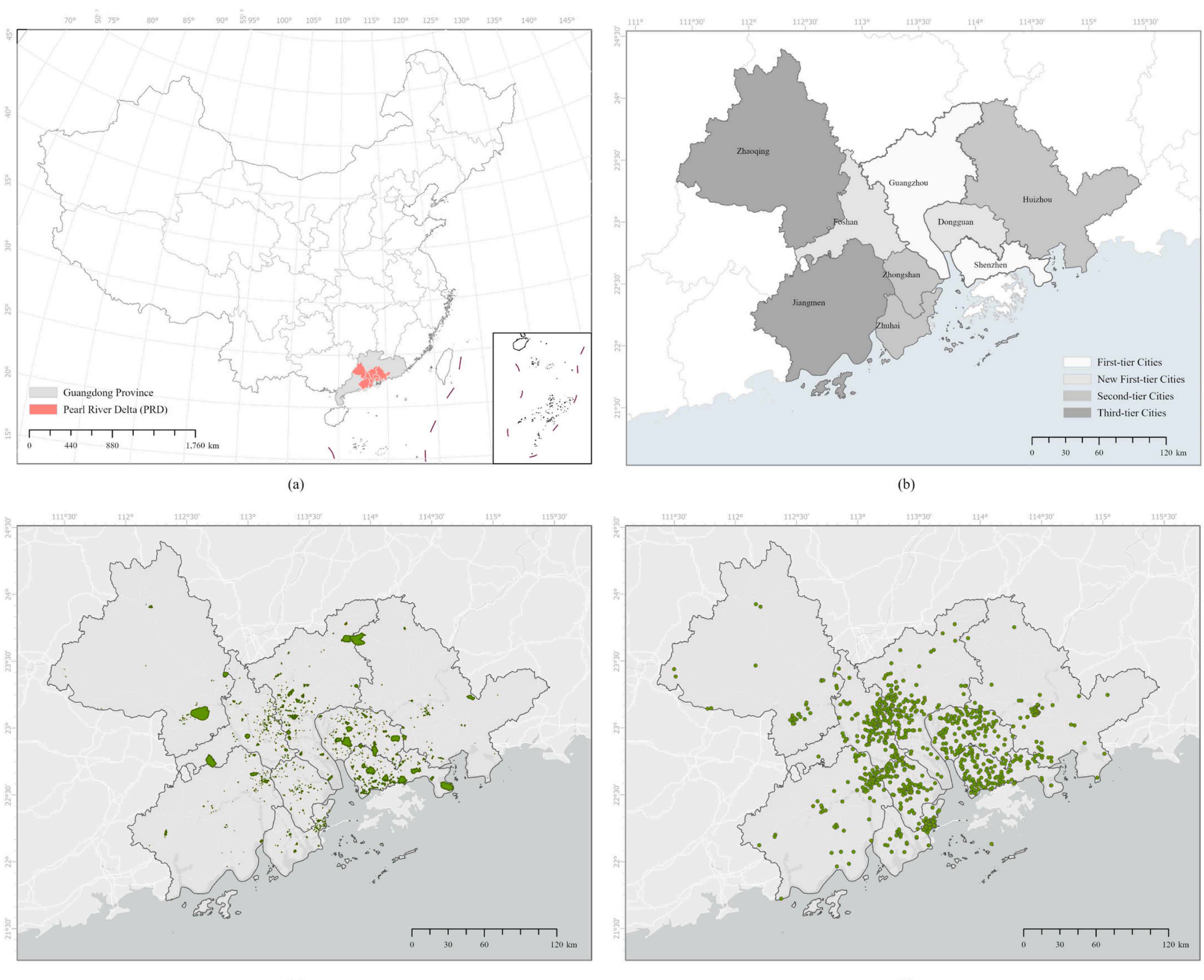

Fig. 1. Mapping of 874 sampled urban parks in the PRD. (a) Geographic location of the PRD in China; (b) Classification of cities within the PRD; (c) Coverage area of the sampled urban parks; (d) Geographic distribution of the sampled urban parks.

Table 1
Classification of cities in the PRD.

Sampled cities	City ranking	The permanent population of year 2021 (10,000 persons)	Gross domestic product (GDP) for year 2021 (100 million CNY)
Guangzhou	First-tier	1881.06	28,231.97
Shenzhen	First-tier	1768.16	30,664.85
Dongguan	New First-tier	1053.68	10,855.35
Foshan	New First-tier	961.26	12,156.54
Zhuhai	Second-tier	246.67	3881.75
Zhongshan	Second-tier	446.69	3566.17
Huizhou	Second-tier	606.60	4977.36
Zhaoqing	Third-tier	412.97	2649.99
Jiangmen	Third-tier	483.51	3601.28

3.2. Variables

3.2.1. Evaluating park visitation

Location-based service (LBS) data has been frequently employed in urban studies in recent years (J. Li et al., 2019; Lyu and Zhang, 2019; Petherick et al., 2021). Compared with surveys or field observations, LBS data offers a novel data source for describing the spatiotemporal behavior of urban dwellers at large scales simultaneously and avoids unconscious sampling bias and inadequate response rates (Cohen et al., 2016; Guo et al., 2019; Sessions et al., 2016). As one type of LBS data, the real-time user density data from applications by companies such as Google and Baidu provide a new method to quantify the spatiotemporal pattern of urban park visitation. In China, Baidu is one of the most popular companies providing everyday services, generating an impressive six billion reactions every day (J. Li et al., 2019). Baidu Heatmap was created to illustrate the spatial distribution of application users' locations offered by Baidu (such as Baidu Search and Baidu Maps). It has been demonstrated to be an accurate and valid proxy for park use and population density in cities by numerous studies (Fan et al., 2021; Fang et al., 2020; J. Li et al., 2019, 2021; Lyu and Zhang, 2019).

Thus, our study used Baidu Heatmap to determine the relative quantity of human activities in urban parks. Following existing research, we collected data of Baidu Heatmap in four days, i.e., between Saturday and Tuesday (November 27, 2021 to November 30, 2021) (Fan et al., 2021; Lyu and Zhang, 2019). The climate during this period was pleasant and sunny. We collected Baidu Heatmap data inside the sample parks based on the park boundaries data every two hours from 7:00–21:00, yielding a total of 293.04 GB of data within the area of sample parks in 32 timestamps, each with a spatial resolution of one meter. The relative quantity of park visitation was calculated using the values in each pixel of the Baidu Heatmap (Lyu and Zhang, 2019). The average park-use value of 32-timestamp was employed as the dependent variable. The calculations were performed in ArcGIS Pro 2.9.1.

3.2.2. Collecting and calculating UGC variables

The UGC dataset in this study consisted of seven major Chinese social media: Sina Weibo, Wechat Media Platform (Wechat MP), TikTok, DaZhong DianPing (DZDP), Ctrip, Bilibili, and Kuaishou.

Sina Weibo, Ctrip, and DZDP provide geotagged features on UGC; users can select a nearby geographic tag (e.g., park, road) when posting and generating geotagged UGC (F. Li et al., 2020). The UGC without geotagged location (i.e., non-geotagged UGC) was also collected from Sina Weibo, Wechat MP, Bilibili, TikTok, and Kuaishou. The non-geotagged UGC is typically accessible to users via keyword searches or push messages by applications. Thus, a total of eight categories of UGC were collected in this study (Fig. 2).

We obtained the park-related UGC displayed on social media platforms, which can simulate how people read UGC from web pages or applications. These data were collected in two ways while strictly adhering to privacy and data security requirements (Fig. 2). The geotagged UGC was gathered via the geotagged pages of sample parks, whereas the non-geotagged UGC was obtained through keyword searches. Eventually, 1,771,093 UGC were collected between November 13 and November 26, 2021. Four steps for UGC data cleaning were included in this study: 1) remove UGC with solely comprises punctuation marks, URLs, digits, emojis, and non-Chinese characters; 2)

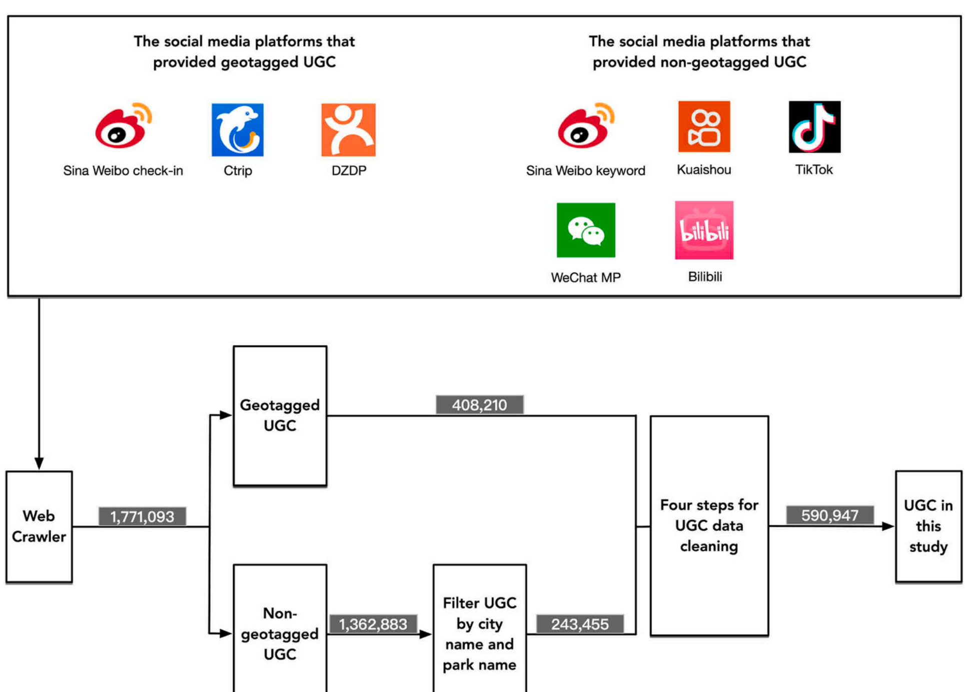

Fig. 2. The framework of UGC collection.

eliminate non-Chinese symbols, URLs, and emojis; 3) exclude content with Chinese characters less than two to mitigate the risk of erroneous classification of sentiment; 4) manual filtering to remove the non park-related UGC. Finally, 590,947 UGC were remained. The data collection and analysis were performed using Python 3.7 with Scrapy and Pandas packages.

This research calculated the rating, sentiment, and exposure as UGC variables. The rating was directly measured from UGC metadata, which was only available for Ctrip and DZDP. Sentiment analysis, which converts ambiguous feelings into quantitative values, can be used to calculate the perceptions and attitudes contained in UGC (Huai and Van de Voorde, 2022). Sentiment analysis was performed using the Baidu Natural Language Processing platform, whose precision has been examined and widely used in various urban studies for measuring Chinese park-related UGC (Cheng et al., 2021; Kong et al., 2022; Wei, Liu, et al., 2023). UGC sentiment ranged from 0 to 2, representing negative, neutral, and positive sentiments, respectively. UGC exposure was determined by calculating the mean number of UGC reads related to the park. The process of calculating UGC exposure is detailed in the Supplementary Materials.

3.2.3. Calculation of park attributes, characteristics of the park surrounding environment, park accessibility, and the control variable

Following previous research, we chose three groups of factors (park attributes, characteristics of the park surrounding environment, and park accessibility) that may influence urban park visitation (Y. Chen et al., 2018; Donahue et al., 2018; Hamstead et al., 2018).

Specifically, park features were evaluated via five indicators. Park areas were calculated from the vector boundaries of the sample parks. The Landscape shape index (LSI) was evaluated to assess the park shape:

$$LSI = \frac{2\sqrt{\pi * Park\_Area}}{Park\_Perimeter}$$

The normalized difference water index (NDWI) and normalized difference vegetation index (NDVI) were employed to measure sample parks' vegetation coverage and water coverage levels based on Landsat-8 satellite images (30x30m per pixel) with Google Earth Engine. The satellite images in the period between November 27, 2020, and November 26, 2021 with no cloud time were collected to calculate the annual NDVI and NDWI composite using the Maximum Value Compositing (MVC) technique (Gorelick et al., 2017). Park facility densities were calculated based on POI densities within the park boundaries.

Park accessibility included six variables. Following previous studies, the density of roads, transport services, and public transit were measured with radii of 500 m (Chiang and Li, 2019). The distances from the urban center were measured to assess the centrality. Moreover, we also used spatial network analysis to examine the topological accessibility. We used sDNA to evaluate the closeness and betweenness with a 500-m radius for measuring the potential for "to-movement" and "through-movement" (Cooper, 2015).

Characteristics of the surrounding environment consisted of eight variables, quantified with a 500-meter straight-line buffer (Y. Chen et al., 2018; Hamstead et al., 2018). Building coverage, mean height, and POI density were used to evaluate the development intensity. Since real estate investment accounts for more than seventy percent of Chinese household wealth (He et al., 2023; Xie and Jin, 2015), the mean housing price was utilized to determine the socioeconomic status (SES) in the surrounding area (He et al., 2021). The population density was then calculated using the number of households in the nearby residential regions. Furthermore, we collected POI data to assess fine-grained land-use status (Yue et al., 2017). Over 2.35 million POIs in PRD were collected with unified classification. We calculated the following index to assess the POI mix (Yue et al., 2017) and measured it as the following equations.

$$D_{richness} = \sum_{i=1}^{s} p_i^0$$

$$D_{entropy} = -[\sum_{i=1}^{s} p_i \ln(p_i)] \Big/ \ln(s)$$

$$D_{simpson} = 1 \Big/ (\sum_{i=1}^{s} p_i^2)$$

Where s is the quantity of POI classification, p_i is the quantity of POIs in the *i*th class.

In addition, to minimize the intervention of tourists from other places on the results, we introduced an "IfTouristAttraction" variable to determine whether the sample park was classified as a tourist attraction. Controlling for the variable IfTouristAttraction allowed us to manage the effect of tourist attractions on the outcomes.

Furthermore, considering the potential influence of urban heat island (UHI) intensity on park visitation (Lin et al., 2023), we controlled for the summer and annual mean UHI intensity of urban parks in the model. We calculated UHI intensity using Landsat-8 satellite images and the following equation.

$$UHI = (LST_{park} - LST_{rural})/LST_{rural}$$

Where LST_{park} is the average land surface temperature within each urban park, LST_{rural} is the mean value of land surface temperature in rural areas.

Table 2 and Table S1 in the Supplementary Materials report the descriptions and descriptive statistics for the above variables.

3.3. Statistical analysis

3.3.1. Kruskal–Wallis test and Dunn–Bonferroni test

First, we examined the differences in UGC variables among four city levels. Since some variables were not normally distributed, the nonparametric Kruskal-Wallis test was employed to compare differences in all variables at the city level. The Dunn-Bonferroni test was then employed for multiple pairwise comparisons.

3.3.2. Getis-Ord Gi* statistic

Second, the Getis-Ord Gi* statistic was employed to investigate the spatial pattern and examine the high- and low-value clusters of UGC variables. The spatial weight was created by K-nearest neighbors of 8 (Ord and Getis, 1995). The calculation equation is as follows.

$$G_i^* = \frac{\sum_{j=1}^{n} w_{i,j} x_j - \overline{X} \sum_{j=1}^{n} w_{i,j}}{S\sqrt{\frac{[n\sum_{j=1}^{n} w_{i,j}^2 - \left(\sum_{j=1}^{n} w_{i,j}\right)^2]}{n-1}}}$$

$$\overline{X} = \frac{\sum_{j=1}^{n} x_j}{n}$$

$$S = \sqrt{\frac{\sum_{j=1}^{n} x_j^2}{n} - (\overline{X})^2}$$

Where x_j is the characteristic for feature j, $w_{i,j}$ is the spatial weight of features i and j, while n equals the total quantity of features.

3.3.3. Linear mixed model

Third, the regression model was employed to reveal the association between park visitation and UGC in different cities. To avoid the bias caused by spatial effects, we conducted pre-tests for all regression models in this study. The Lagrange multiplier pre-test and Moran's I test

Table 2
The descriptions of park attributes, characteristics of the park surrounding environment, park accessibility, and the control variable.

Categories	Variables	Descriptions	Data Sources
Park attributes	AREA	Area of urban park	Polygon shape files of parks based on Baidu API
	LSI	Landscape Shape Index	
	NDWI	Normalized Difference Water Index	Landsat-8 satellite images (30x30 m per pixel) from 27/11/2020–26/11/2021
	NDVI	Normalized Difference Vegetation Index	
	ParkFacility	Density of facilities in the park	Geographic POI data based on Baidu API
Accessibility	RoadDen	Density of surrounding roads	Road vector data of PRD in 2021
	StopDen	Density of surrounding bus and metro stops	Geographic POI data based on Baidu API
	TransServiceDen	The density of surrounding transportation services, such as parking lot	
	DisUC	Distance from the urban center	Distance between park centroid and urban center
	Closeness	Measuring the "to-movement" potential.	Road vector data of PRD in 2021
	Betweenness	Measuring the "through-movement" potential.	
Characteristics of the surrounding environment	BuildCoverDen	Surrounding building cover density	Building vector data of PRD in 2021
	MeanH	The mean height of the surrounding building	
	POIDen	Surrounding POI density	Geographic POI data based on Baidu API
	POIRichness	Surrounding POI richness	
	POIEntropy	Surrounding POI entropy	
	POISimpson	Simpson index of surrounding POI	
	PopDen	Surrounding household density	Residential housing data in 2021
	SES	Surrounding house price	
Control variable	IfTouristAttraction	If a sample urban park is listed as a tourist attraction	The dictionary of tourist attractions provided by the Municipal Bureau of Culture, Radio, Television, Tourism and Sports of the PRD cities
	UHI_year	Average urban heat island intensity in 2021	Landsat-8 satellite images (30x30 m per pixel) in 2021
	UHI_summer	Average urban heat island intensity in 2021 summer period	

showed insignificant ($p > 0.05$) (Anselin et al., 2010).

Thus, we used the linear mixed model to consider the hierarchical data structure and examine the fixed effects of UGC variables on all urban parks in nine PRD cities. Linear mixed model emerges as a preferred method for performing association analyses in scenarios involving sample structure (e.g., geographic population structure). Through examining fixed and random effects in the model, linear mixed model demonstrates effectiveness in minimizing false-positive relationships attributed to population or relatedness structure (Yang et al., 2014). It is formulated as follows (Bates et al., 2015).

$$Y_{ij} = \beta_0 + \beta_1 X_{1ij} + \beta_2 X_{2ij} + \ldots + \beta_k X_{kij} + u_{0j} + \varepsilon_{ij}$$

Where Y_{ij} represents the response variable (i.e., urban park use) for the i-th observation in the j-th city; $\beta_0$is the fixed intercept; X_{1ij}, X_{2ij}, …, X_{kij} represent the values of the k predictor variables for the i-th observation in the j-th city; β_1, β_2, …, β_k are the fixed coefficients for the k predictor variables, representing the effect of each predictor on the response variable; u_{0j} represents the random intercept for the j-th city, capturing the city-specific deviation from the overall average; ε_{ij} is the residual term, representing unexplained variability at the individual observation level.

To ensure a normal distribution of the data, we calculated the natural logarithm of the park use value. The variation inflation factor (VIF) investigated the multicollinearity between the dependent variables; we eliminated the variables with a VIF greater than 5. In our model, we considered the random effects for various cities to manage the unpredictable variations in diverse urban settings. Three sets of analyses were conducted after adjusting for other covariates. First, we proceeded to assess the fixed effects of variables on park visitation across nine cities. Model 1 functioned as the baseline model, which included all covariates and the control variable. Models 2–4 further added the UGC sentiment, exposure, and rating variables, respectively. Second, based on the Standard of Classification of Urban Green Space (CJJ/T85–2017) in China, urban parks can be divided into comprehensive parks and community parks, respectively. We further investigated UGC's effects on park visitation in different types of urban parks. Third, given that different city levels have different situations (e.g., urban development, population density, economic status), we developed subgroup regressions to examine the differences in the effects of variables on park visitation across different city levels. We further evaluated the significance of differences in variable effects across city tiers by constructing interaction terms with categorical variable for the city level (Bates et al., 2015).

The lme4 package in R v4.0.5 was used for modeling.

4. Results

4.1. Imbalance in the distribution of UGC variables in cities at different levels

The UGC related to sample parks is distributed unevenly over seven social media platforms. There are 222 parks that had UGC throughout all platforms; 632 parks had UGC on one to seven platforms. There was no UGC for 20 parks on each platform (Fig. 3a). The quantity of sample parks on each platform varied between 355 and 801 (Fig. 3b). The distribution of UGC related to sample parks varied significantly, ranging from 6,911 to 220,916 (Fig. 3c).

The distribution of overall UGC factors showed significant differences at different city levels (Fig. 4). Specifically, the values of park-related UGC rating, sentiment, and exposure decreased as the city level dropped. The hypothesis of equal distribution of UGC variables across the city level was rejected (Kruskal-Wallis test, $p < 0.001$). The Dunn test further indicated that the first-tier cities had significantly higher UGC rating, sentiment, and exposure compared to other city levels ($p < 0.001$); the level of UGC exposure in new first-tier cities

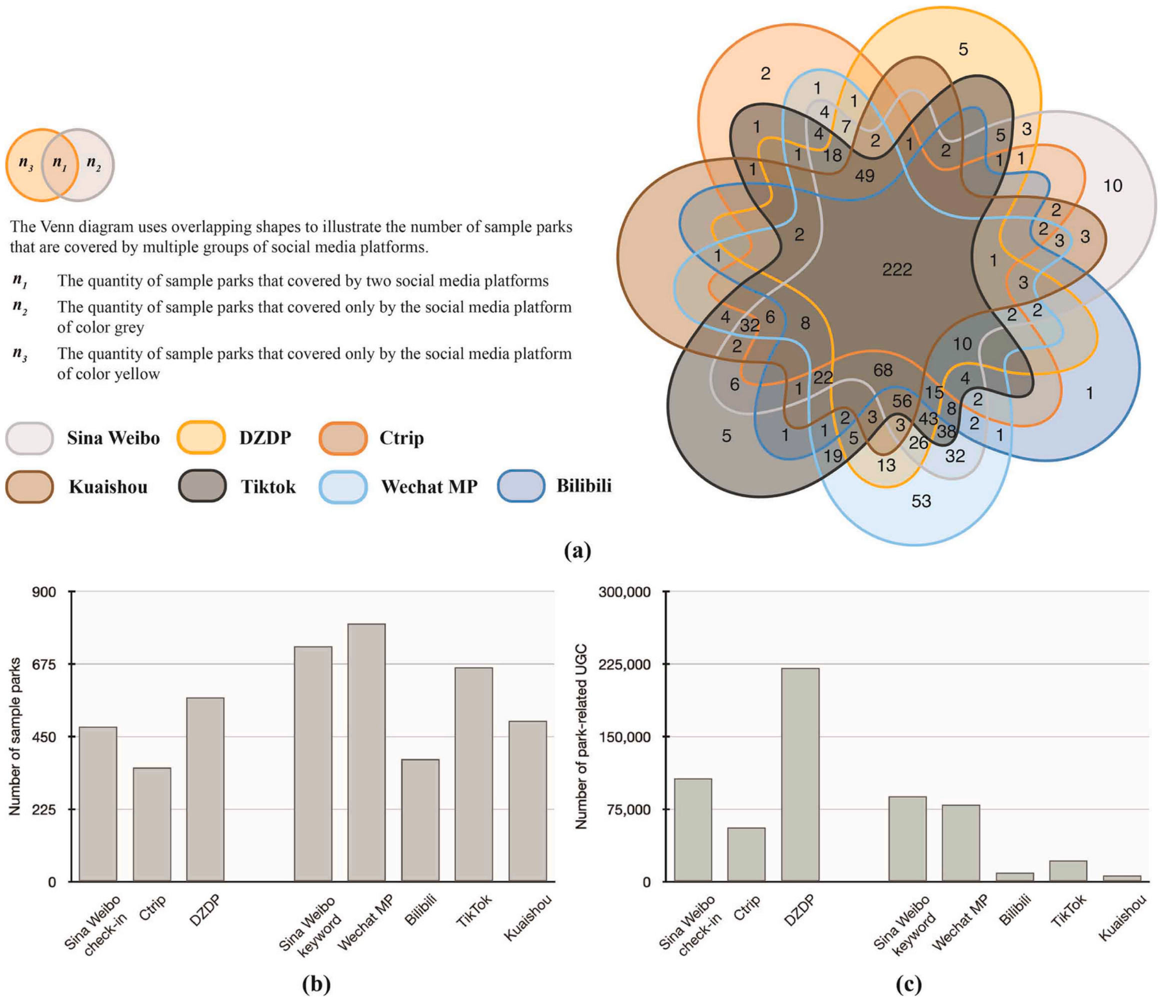

Fig. 3. Distribution of park-related UGC and the sample parks across the seven social media platforms and the eight categories of UGC. (a) The Venn diagram illustrating the number of sample parks covered by the seven social media platforms; (b) The number of sample parks that have park-related UGC in the eight categories of UGC; (c) The number of park-related UGC in the eight categories of UGC.

significantly exceeded that observed in second-tier and third-tier ($p < 0.001$) (Table S2).

The results of the Getis-Ord Gi* statistic (Fig. 5) indicated the significant spatial heterogeneity of overall UGC variables in PRD. The rating, sentiment, and exposure of park-related UGC had significant high-value clustering patterns in first-tier and new first-tier cities. Besides, the significant low-value clustering pattern of UGC sentiment and rating was found in cities other than the first-tier cities.

4.2. Estimating the effects of UGC on urban park visitation

By fitting four linear mixed models (Table 3), we examined the fixed effects of UGC on park visitation among different cities of PRD. The baseline model (Model 1) demonstrates a high degree of model fit (Marginal $R^2 = 0.715$). After adding UGC factors (rating, sentiment, exposure), the overall explanatory power of Model 2–4 had significant increases when compared to those of Model 1 (ANOVA Chi-Square of R^2 change, $p < 0.001$); the marginal R^2 for Model 2–4 were 0.760, 0.773, 0.736, respectively. The significant fixed effects showed that UGC variables had positive effects on park visitation in the PRD cities. Notably, the highest fixed effect of UGC was 0.240 (Rating of DZDP); it stands out as the second-highest effect among all variables in the model, surpassed only by the effect of NDVI at 0.356. In addition, the highest fixed effects for UGC sentiment, rating, and exposure variables were 0.240, 0.080, and 0.127, respectively, which suggested that UGC rating exerted a greater effect on park visitation than UGC sentiment and exposure.

In addition, Table S3 and S4 reported the effects of UGC variables on comprehensive park visitation and community park visitation, respectively. Our finding indicated that UGC exposure, rating, and sentiment had significant effects on comprehensive park visitation. However, no UGC variable had a significant effect on the visitation of community parks.

Furthermore, we examined the fixed effects of UGC in first-tier, new first-tier, second-tier, and third-tier cities in the PRD, respectively (Table S5 to Table S8). Notably, we observed a declining trend in the effects of UGC variables with a decrease in city level (Fig. 6). Specifically, the effects of SinaWeibo check-in sentiment, Kuaishou sentiment, and Bilibili sentiment on park visitation vary significantly across different city levels (Table S9). Besides, although the effects of remaining UGC variables had a decreasing trend with a decrease in city level, the difference in their effects was not significant.

4.3. Estimating the effects of park attributes, characteristics of the park surrounding environment, and park accessibility on urban park use

The high marginal R^2 observed in Model 1 indicated a significant association between park visitation and a combination of park features, surrounding environmental characteristics, and park accessibility (Table 3). In detail, all variables of park attributes, such as area, NDWI, NDVI, LSI, and density of facilities in the park, exhibited significant fixed

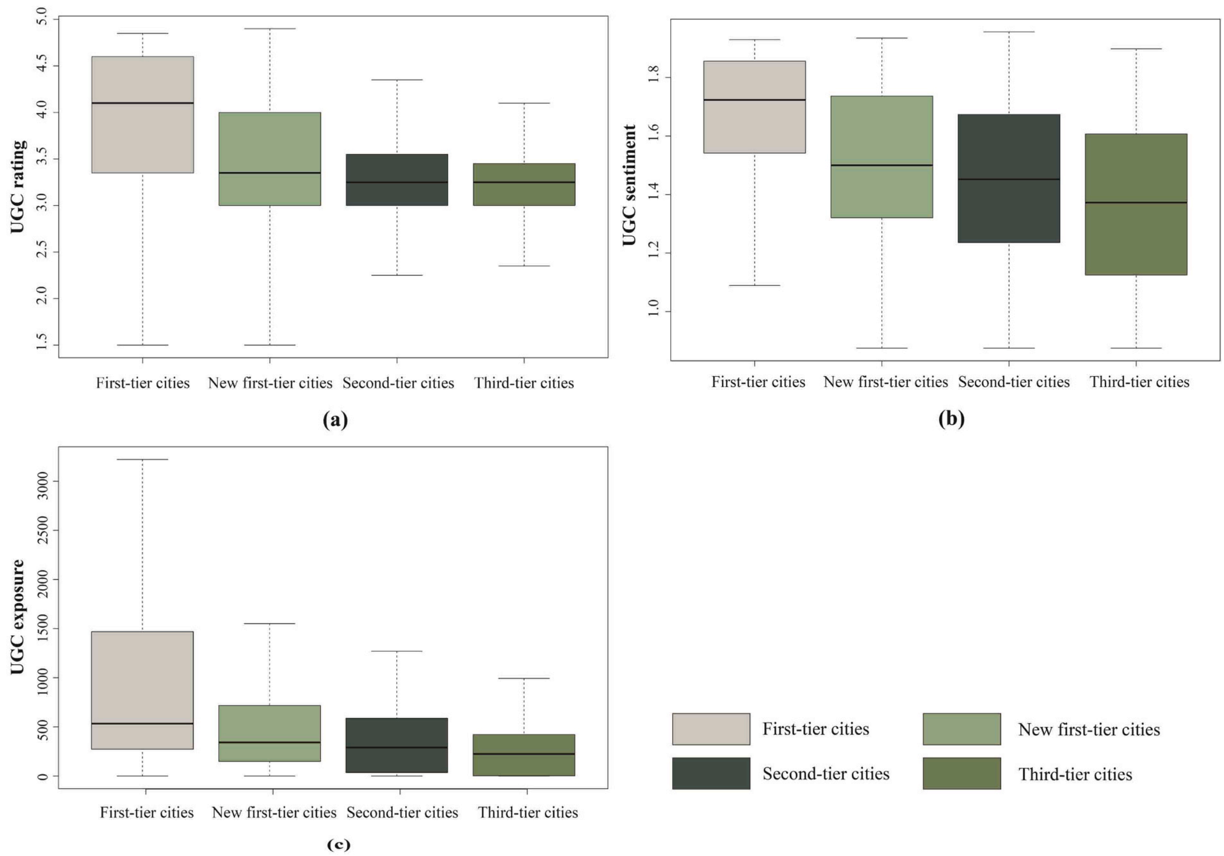

Fig. 4. Boxplots illustrating UGC variables in the 874 parks across different city levels. (a) Overall values of UGC rating; (b) Overall values of UGC sentiment; (c) Overall values of UGC exposure.

effects on park use. Furthermore, transport service density, distance to the urban center, closeness, building coverage, population density, and density and entropy of POI exhibited significant fixed effects on park visitation. Notably, the fixed effect of NDVI (0.403) was the highest of all variables in the Model 1.

In addition, we examined the fixed effects of park attributes, characteristics of the park surrounding environment, and park accessibility on park visitation across different city levels in the PRD (Table S5 to Table S8). We observed an increasing trend in the effects of some variables with a decrease in city level (Fig. 7). Specifically, the effects of NDWI, SES, road density, and transport service density on park visitation vary significantly across different city levels (Table S10). Although the effects of closeness had an increasing trend with a decrease in city level, the difference in its effect was not significant.

5. Discussion

5.1. The effects of UGC variables on park visitation

Our finding suggested that the park-related UGC variables may significantly affect park visitation at all city levels in PRD (Table 3). Notably, UGC showed high coefficients, with UGC rating being the second highest (0.240). This is higher than key factors such as park accessibility and surrounding environment confirmed in previous studies (Donahue et al., 2018), highlighting the crital role of UGC in increasing park use in modern society.

Moreover, our results showed that UGC from Sina Weibo, DZDP, Bilibili, TikTok, Kuaishou, and Ctrip had significant positive effects. Compared to previous park-related studies that focused only on geotagged UGC variables in one or two social media platforms (Donahue et al., 2018; Hamstead et al., 2018; Lyu and Zhang, 2019), our study discovered significant effects of UGC in six out of seven mainstream Chinese social media platforms. Simultaneously, we identified the effects of both geotagged and non-geotagged UGC on park visits. Our results complement the evidence for UGC effects on park use. However, we observed variations in UGC's effects across different social media platforms. We speculated that the discrepancies may stem from variations in the demographics and age distribution of users, exposure mechanisms, and other characteristics among various social media platforms (Statista, 2023).

Furthermore, we found that UGC had greater significant coefficients on comprehensive park visitation than on community park visitation, which may stem from differences in residents' preferences for visiting various park types and the corresponding service radius of each type of parks. Comprehensive parks feature a broader service radius, catering to a diverse urban population with varied visitation intentions, such as following hiking trails, exploring landmarks, admiring views, or engaging in various activities (Tieskens et al., 2018). Consequently, UGC offers real-time information and on-site experience sharing, which may have significantly affected residents' decision-making for comprehensive park visitation (Narangajavana Kaosiri et al., 2019). Conversely, visitation to community parks typically comprises routine visits by residents from nearby neighborhoods (Z. Zhang et al., 2021) and may be less affected by UGC.

In addition, compared to UGC quantity employed by previous studies (Wilkins et al., 2021), using other UGC variables (e.g., exposure, rating, and sentiment) to assess UGC's effects may be less susceptible to bidirectional effects (Wei, Wang, et al., 2023). Existing evidence between UGC quantity and park visitation could be influenced by bidirectional effects (Imbens and Rubin, 2015); an increase in park visitation may lead to an increase in UGC quantity, and vice versa. While increased park visitation may increase UGC quantity and lead to both more

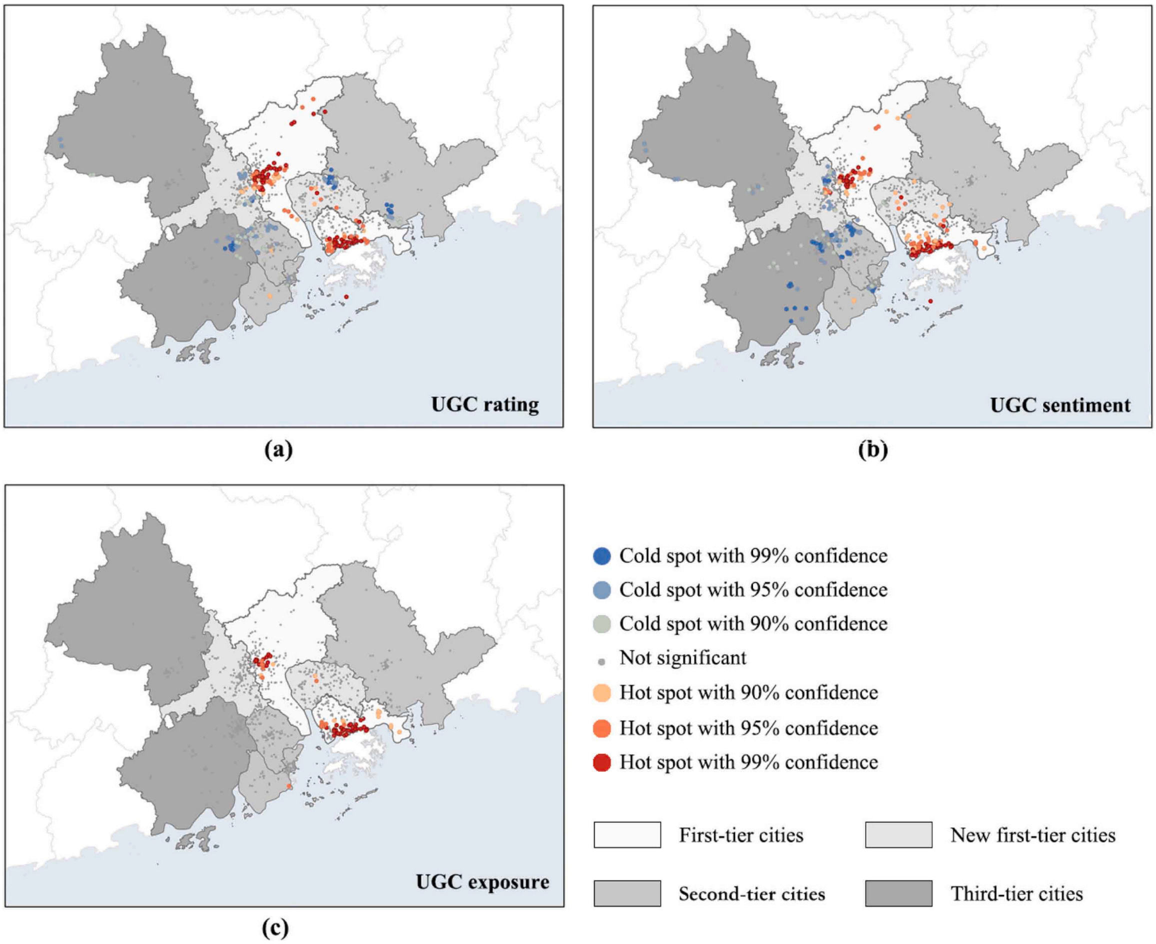

Fig. 5. The spatial pattern of UGC variables calculated by the Getis-Ord Gi* statistic. (a) Spatial clusters of overall UGC rating; (b) Spatial clusters of overall UGC sentiment; (c) Spatial clusters of overall UGC exposure. The majority of high-value clustering of UGC variables was concentrated in the first-tier cities, while low-value clustering occurred in non-first-tier cities.

positive and negative UGC reviews, the overall UGC sentiment and rating (i.e., the average value of UGC sentiment and rating per park) may not be influenced by park visitation (Wei, Liu, et al., 2023). Furthermore, previous studies suggested that UGC exposure is affected by exogenous variables, such as traffic and the popularity of the UGC contributor or social media platform algorithms, rather than park visitation (Pop et al., 2021; Wei et al., 2023). Thus, after controlling for the confounders, we could infer relatively reliable UGC's effects on park visitation through UGC exposure, rating, and sentiment. However, this study still did not provide causal evidence of UGC's effects on park visitation and required attention in subsequent studies.

We tentatively proposed two potential explanations for the effects of park-related UGC on park visitation. 1) UGC could redistribute park visitors to different parks. Positive park-related UGC sentiment and rating may increase the potential users' favorable opinion and willingness to visit a park, which aligns with previous studies (Almeida-Santana and Moreno-Gil, 2017; Xiang et al., 2015). In addition, UGC ratings reflect users' overall sentiment about the park and are often placed most prominently on destination-specific pages. People can compare the ratings to make quick travel decisions instead of reading every UGC. This may also explain our results that the rating has a greater effect on park visitation than the sentiment. 2) UGC may induce additional park use by attracting new people to visit parks. The notable effect of UGC exposure suggested that the UGC could positively affect people who read the UGC for decision-making about park visitation. It echoes one previous study using the survey (Pop et al., 2021) that greater exposure to UGC may affect individuals' intentions, specifically by fostering more positive attitudes toward specific destinations.

5.2. *The effects of UGC variables at different city levels*

We found that the higher the city level, the greater the UGC's effects on park visitation (Fig. 6). The results align with previous research that the effect of potential variables influencing park use may vary in different urban contexts (Donahue et al., 2018). It reaffirms the notion that the UGC factors we focus on may not exert same effect on park visitation, like other built environment variables (F. Li et al., 2020), but rather depend on the specific city level under consideration.

We speculated that this phenomenon could be attributed to three potential reasons. First, the difference in the UGC effect on park visitation across different cities may be attributable to variations in social media usage rates among these cities. Existing statistical data indicated that the first-tier and new first-tier cities exhibit a higher proportion of social media users compared to other city levels in China (Statista, 2022). Furthermore, our spatial analysis results also supported similar findings that parks with high-UGC exposure significantly clustered in the first-tier and new first-tier cities (Fig. 5). Such higher social media usage and readership of park-related UGC in higher city levels may lead to a higher effect of UGC on residents in higher city levels, thereby resulting in a more pronounced effect of UGC on park use in higher city levels.

Second, the age proportion across different city levels may also contribute to the heterogeneous results in UGC effects. Existing research supports our hypothesis, suggesting that UGC tends to have higher

Table 3
The linear mixed model of park visitation in nine cities in PRD (N = 874). After controlling for the confounders, the rating, sentiment, and exposure of park-related UGC exerted significant effects on park visitation.

Model Predictors	Model 1	Model 2	Model 3	Model 4
Fixed Effects				
Park attributes				
AREA	0.190 ***	0.193 ***	0.185 ***	0.195 ***
LSI	-0.129 ***	-0.116 ***	-0.111 ***	-0.121 ***
NDWI	0.232 ***	0.198 ***	0.181 ***	0.213 ***
NDVI	0.403 ***	0.356 ***	0.345 ***	0.396 ***
ParkFacility	0.155 ***	0.105 ***	0.129 ***	0.119 ***
Park accessibility				
RoadDen	0.052 *	0.017	0.029	0.041
StopDen	0.022	0.009	0.014	0.010
TransServiceDen	0.093 ***	0.051 *	0.049 *	0.076 **
DisUC	0.047 *	0.049 *	0.05 **	0.038
Closeness	0.044 *	0.042 *	0.039 *	0.037 *
Betweenness	-0.007	-0.014	-0.013	-0.013
Characteristics of the surrounding environment				
BuildCoverDen	-0.046	-0.055 *	-0.031	-0.050 *
MeanH	0.021	0.023	0.010	0.015
POIDen	-0.301 ***	-0.244 ***	-0.249 ***	-0.272 ***
POIRichness	0.011	0.024	0.020	0.027
POIEntropy	-0.057 *	-0.073 **	-0.065 **	-0.063 *
POISimpson	0.033	0.041	0.033	0.040
PopDen	0.062 *	0.056 *	0.053 *	0.066 **
SES	0.032	-0.009	0.008	0.014
Control variable				
IfTouristAttraction	0.146	0.080	0.084	-0.025
UHI_year	-0.127 ***	-0.098 ***	-0.094 ***	-0.119 ***
UHI_summer	-0.013	-0.005	-0.011	-0.025
User-generated content				
Rating_DZDP		0.240 ***		
Rating_Ctrip		0.045 *		
Sentiment_SinaWeiboCheck-in			0.080 ***	
Sentiment_DZDP			0.021	
Sentiment_Ctrip			0.072 **	
Sentiment_SinaWeiboKeyword			0.044 *	
Sentiment_WechatMP			0.014	
Sentiment_Kuaishou			0.073 ***	
Sentiment_Tiktok			0.043 *	
Sentiment_Bilibili			0.062 **	
Exposure_SinaWeiboCheck-in				0.127 ***
Exposure_SinaWeiboKeyword				0.019
Exposure_Kuaishou				0.049 **
Exposure_TikTok				0.006
Exposure_Bilibili				0.043 *
Random Effects				
σ^2	0.26	0.23	0.22	0.25
τ_{00}	0.02	0.01	0.01	0.02
ICC	0.07	0.06	0.03	0.06
N	9	9	9	9
Marginal R^2	0.715 ***	0.760 ***	0.773 ***	0.736 ***
ANOVA Chisq of R^2 change		132.980 *** (vs. Model 1)	169.150 *** (vs. Model 1)	59.967 *** (vs. Model 1)

Note: * indicates $p < 0.05$, ** indicates $p < 0.01$, *** indicates $p < 0.001$.

effects on the behavior and choices of younger individuals, particularly in Generation Y (born from 1980 to 1994) and Generation Z (born from 1995 to 2010) (Pop et al., 2021). According to the statistics from the PRD, the proportions of the population aged 15–40 vary across different city levels: 0.507 in first-tier cities, 0.474 in new first-tier cities, 0.428 in second-tier cities, and 0.337 in third-tier cities (Guangdong Bureau of Statistics, 2022). This may result in a higher city level with a higher proportion of younger individuals experiencing higher effects of UGC on park visits.

Third, the varying proportions of the non-local population across different city levels may contribute to heterogeneity in UGC effects. We speculated that the non-local population may not be as familiar with the city, and thus, they might be more inclined to make decisions about urban park visitation through UGC. Our speculation aligns with existing research, which suggests that when people are unfamiliar with a specific destination, UGC has a higher effect on their travel decision-making (Tsiakali, 2018; Y. Zhang et al., 2021). According to the 7th National Population Census of China, the proportions of the non-local population to the total population in the PRD were 0.658, 0.655, 0.513, and 0.219 for first-tier cities, new first-tier cities, second-tier cities, and third-tier cities, respectively (Guangdong Bureau of Statistics, 2022). Thus, the trend of decreasing non-local population proportion with the decrease in city level may result in a reduction of UGC effects.

5.3. The effects of park attributes, characteristics of the park surrounding environment, and park accessibility

Our results indicated that park attributes, characteristics of the park surrounding environment, and park accessibility had significant effects on park visitation (Table 3). Specifically, all variables of park attributes, such as area, NDWI, NDVI, LSI, and the density of park facilities, exhibited significant effects on park use. This aligns with existing research, suggesting that increased park size, intricate park shapes, higher green and water coverage, and diverse park service facilities significantly enhance park visitation (Y. Chen et al., 2018; F. Li et al., 2020; Veitch et al., 2022). Furthermore, certain findings of characteristics of the park surrounding environment and park accessibility are also in line with existing research; enhanced transport services, increased topological centrality, and higher surrounding population density significantly contribute to the promotion of park visitation (Chiang and Li, 2019; Cooper, 2015; Guo et al., 2019). However, we observed that greater distance from the city center, lower building density, and lower levels of POI density and POI entropy in the surrounding area were significantly associated with higher park visitation. This could be because it is more conducive to creating a natural and tranquil environment for the park, allowing people to escape the urban hustle and bustle, and enhancing the park's natural beauty, thereby attracting urban residents (Lu et al., 2021). In addition, lower POI density and POI entropy may imply fewer recreational facilities in the surrounding area, making the park the primary focus for recreational activities in that area.

Moreover, we observed a trend in which the effects of certain variables (NDWI, SES, road density, transport service density, and closeness) increased with the decrease in city levels (Fig. 7). The effect of factors influencing park visitation may vary across different urban contexts (Donahue et al., 2018). It is noteworthy that this trend of increasing effects as city level decreases was opposite to the trend of decreasing UGC effects as city level decreases. Hence, compared to UGC variables, second and third-tier cities should place more emphasis on the effects of built environment factors, especially accessibility, on park use.

6. Conclusion

This research explored the spatial pattern of UGC and the relationship between UGC and park visitation across a broad scale, encompassing multiple cities in China. The findings revealed that the UGC

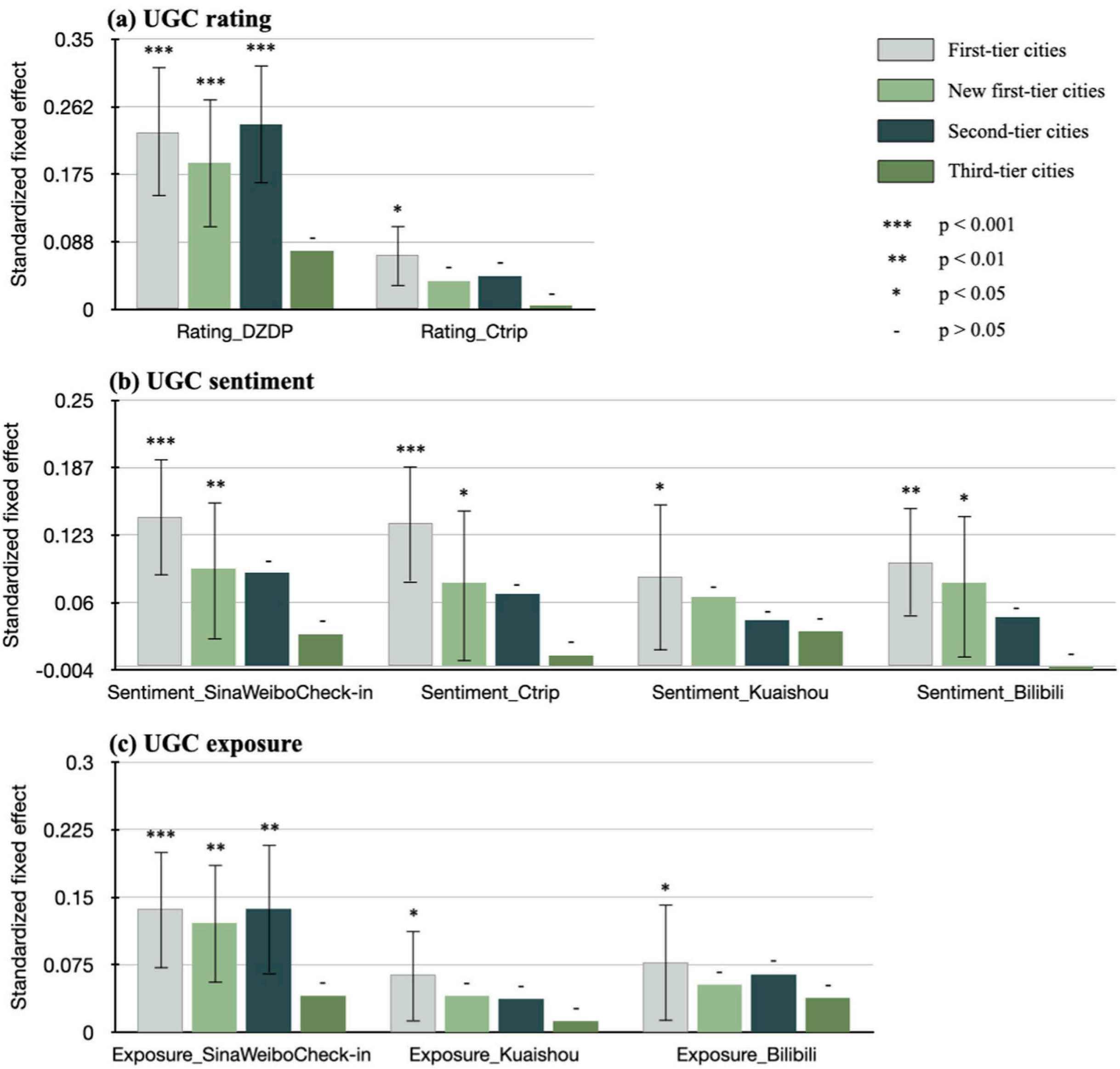

Fig. 6. The effects of UGC variables on park visitation across different city levels after controlling for the confounders. (a) The standardized fixed effects of UGC rating; (b) The standardized fixed effects of UGC sentiment; (c) The standardized fixed effects of UGC exposure. The majority of UGC variables exhibited the strongest effects on park visitation in the first-tier cities, with a decreasing trend in the effect of UGC variables as the city level decreases.

variables had significant effects on park visitation in all city levels. UGC rating had greater effects on park visitation than sentiment and exposure. In addition, we revealed differences between different city levels and discovered spatial heterogeneity in UGC variables. It is noteworthy that we have identified two trends: a decreasing trend in the effects of UGC variables with the decline in city level and a rising trend in the effects of certain built environment variables with the decrease in city level.

6.1. Contribution and implication

Our results suggest that UGC stands out as an indispensable key factor in maximizing urban park visitation in modern society and should be appropriately examined in future analysis, planning, and management.

First, we observed significantly positive effects of park-related UGC exposure, sentiment, and rating on park visitation across various city tiers in China. Thus, we recommend urban management authorities improve the publishing and dissemination of park-related UGC through various methods, such as improving internet infrastructure in parks, setting up UGC information boards for public engagement, hosting hybrid online-offline events, using official accounts to post UGC and boost public involvement. UGC rating's effect on park visitation is the second highest in the model and deserves particular attention from park management. Furthermore, considering that UGC was significant primarily in comprehensive park visitation but not in community parks, we suggest prioritizing the above strategies for comprehensive parks.

Second, although UGC may boost park visitation, built environment factors remain significant, warranting attention to the following significant factors and allocating urban public resources sensibly. Specifically, greenery coverage exhibits the highest positive effect on park visitation (standardized coefficient = 0.403), which deserves particular attention. In addition, park area, water coverage, landscape shape index, density of park facilities, surrounding road density, transportation service density, topological centrality of surrounding roads, and population density may also significantly enhance park visitation. Moreover, appropriately reducing building density, POI density and entropy around urban parks may contribute to creating a natural and tranquil environment and boost

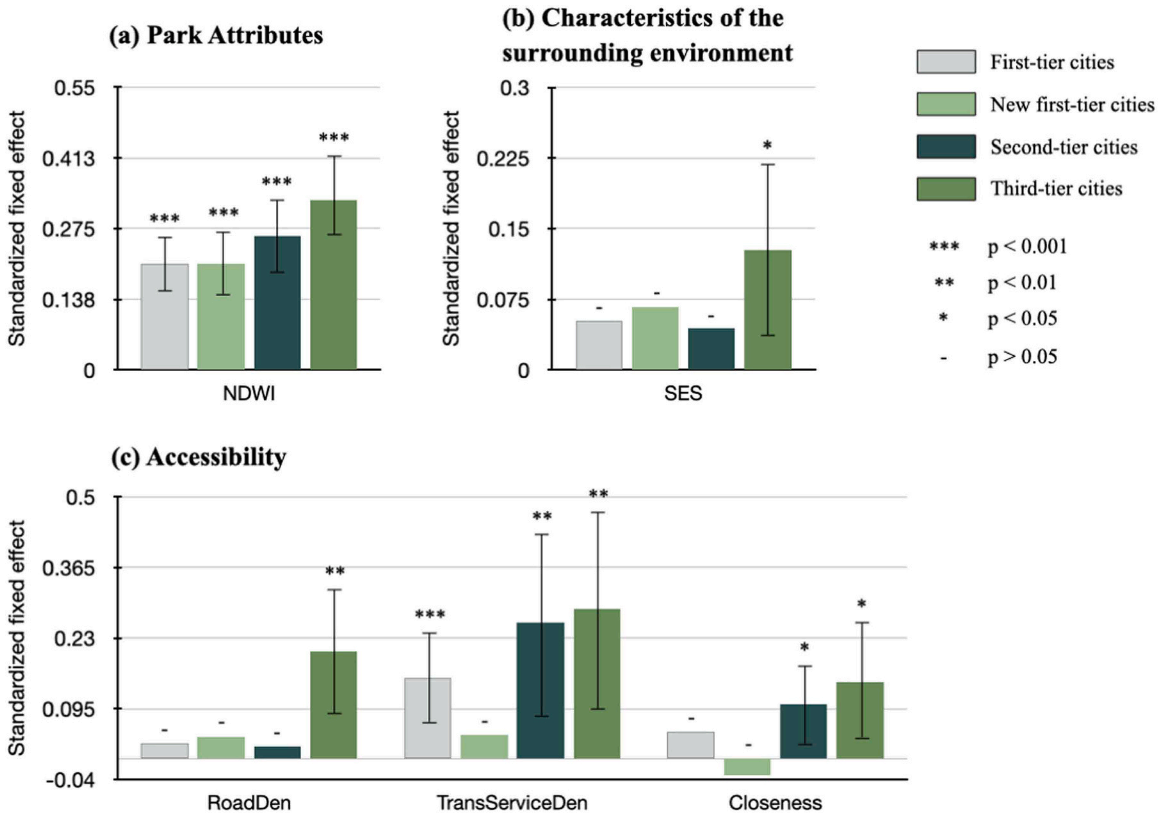

Fig. 7. Some variables demonstrated increasing effects on park visitation as city levels decreased. (a) NDWI in park attributes; (b) SES in the characteristics of the surrounding environment; (c) road density, transport service density, and closeness in park accessibility.

park visitation.

Third, we observed that the effects of UGC decrease as city level declines, whereas the effects of some built environment factors increase as city level declines. Hence, we suggest that urban parks in first-tier and new first-tier cities should focus more on UGC's effects on park visitation. Conversely, second-tier and third-tier cities should prioritize the improvement of the built environment, including increased water coverage, surrounding road density, transportation service density, and the topological centrality of surrounding roads.

6.2. Limitations

It is important to consider several limitations. First, this study used the data from Baidu Heatmap as the proxy of park visitation among nine cities in PRD. Despite the high accuracy and numerous advantages offered by Baidu Heatmap data, it lacks individual-level data and social-demographic attributes of park users. This may result in including some individuals who simply pass through a park in visitation data. Also, we are unable to analyze the influence of social-demographic factors on park visitation. Thus, further studies with individual-level data are needed to address this limitation. Second, we investigated how UGC may influence park visitation in nine cities of different city levels in China. However, further investigation is required to determine the applicability of our conclusions to cities outside of China. Furthermore, this study only revealed the heterogeneity effect of UGC and built environment on park visitation among different city levels. Future studies need to incorporate statistical models such as structural equation modeling or Bayesian networks to further infer the underlying mechanisms of such heterogeneity. Third, although our study inferred that UGC could influence park visitation through the significant effects of UGC exposure, sentiment, and rating, it is crucial to recognize that this study cannot provide causal evidence between UGC and park visitation. Future studies need to conduct well-controlled interventions or natural experiments to address this issue.

Declaration of Competing Interest

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

Data Availability

Data will be made available on request.

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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.landusepol.2024.107259.

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