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Could There Be Negative Sentiments Toward Urban Parks? An Analysis of Internal and External Factors.

Abstract: Urbanization and its associated stressors have amplified the importance of mental health. Urban parks serve a vital function in mitigating adverse emotions and fostering emotional well-being. Nevertheless, inadequate maintenance and poor landscape design often result in unfavorable public perceptions of these parks. While previous studies have predominantly examined the positive emotional benefits of urban parks, this research seeks to investigate the negative sentiments linked to these spaces, focusing on both their internal and external attributes that may contribute to such perceptions. This study analyzed 83 urban parks in the main districts of Nanjing city, employing sentiment analysis on Weibo microblog posts through natural language processing techniques to assess public negative sentiments. Multiple linear regression models were employed to investigate the relationship between the internal and external characteristics of urban parks and public negative sentiments. The results revealed significant relationships between physical attributes, landscape visual quality, accessibility, built-environment density as well as park management and the negative sentiments reported by the public. These findings inform the planning and management of urban parks to enhance the emotional well-being of the public.

Keywords: urban parks; negative emotions; sentiment analysis; mental health; landscape attributes

1. Introduction

The intensification of societal challenges such as climate change and pandemics has led to a sustained increase in global attention on public health (Liu et al., 2023). Particularly in urban areas, where rapid urbanization and population pressure exacerbate the challenges to physical and mental well-being, there is an increasing necessity to understand and address the emotional health of the public (Galea et al., 2005). Studies show that emotions consist of three main types: positive, negative, and neutral (Frijda, 1986). These emotions arise from how people perceive and evaluate situations. This highlights the intricate interplay between an individual's psychological state and their environment.

Positive emotions have been shown to have beneficial impacts on individuals and society, including enhancing psychological resilience, physical health, and fostering social harmony (Fredrickson, 2004). Conversely, negative emotions play a more complex role in mental health, acting as an intermediary between external stressors and individual psychological well-being. Improper handling of these emotions can not only affect personal health but also exacerbate the negative impacts of adverse social events (Xu & Huang, 2022). Therefore, addressing the public's negative emotions and promoting positive emotions are conducive to strengthening social cohesion and improving overall well-being, thereby serving as a fundamental element for sustainable urban development.

Urban parks, as vital components of green space, offer more than just venues for recreational activities; they hold significant importance for psychological well-being, ecological balance, economic vitality, and cultural enrichment (Wolch et al., 2014). Nevertheless, many visitors report negative experiences related to urban parks, which can be attributed to poor landscape design, improper management strategies, and ecological issues (Wan et al., 2024). This trend has been widely documented across various news outlets and social media platforms globally. For instance, Marble Arch Hill in London, designed by MVRDV, was forced to close merely two days after its inauguration in 2021 due to unfavorable reviews, with the landscape's condition being criticized as "a considerable waste of time and resources" (NetEase, 2021). Similarly, the Nanjing Peace Park West Garden, once celebrated as a prime location for relaxation and leisure for local residents, has faced backlash on the Chinese news aggregation site Toutiao due to insufficient upkeep and management of its water features and plant life, leading to environmental decline (Qian, 2015). Such concerns call for better design and management of urban parks to mitigate their negative emotional impacts on the public, thus promoting emotional well-being (Jang et al., 2024; Wolch et al., 2014).

So far, research related to urban parks has primarily focused on examining the connections between urban parks and the public's spatiotemporal activities (Fan et al., 2021; Kovacs-Györi et al., 2018; Li et al., 2023), physical and mental health (Cheng et al., 2021; Deng et al., 2020; Kaklauskas et al., 2021; Wu et al., 2023), satisfaction assessments (Li et al., 2023; Liu & Xiao, 2020; Wang et al., 2021), and urban sustainable development (Dai et al., 2019; Yu et al., 2023). Within these studies, the dimension of public emotions has garnered particular attention, with scholars attempting to uncover the impact of natural and socioeconomic factors, such as pandemics and air quality in urban parks, on the public's emotional experiences (Cheng et al., 2021; Shan et al., 2021). However, the majority of research focuses on data pertaining to positive emotions, a phenomenon that may likely arise from the "positive bias" inherent on social media platforms (Fernandez et al., 2022; Shao et al., 2017; Wang et al., 2021). Users tend to share content that they believe will enhance their social appeal or align with their self-image (Huai et al., 2023). Additionally, existing studies have predominantly focused on the impact of a singular dimension of elements in urban parks on emotions, such as either natural or socioeconomic factors, and have not yet constructed a comprehensive evaluation system.

This study seeks to explore the correlation between the landscape attributes of urban parks and the negative emotions experienced by the public, using textual analysis of social media data sourced from urban parks within the main districts of Nanjing city. The originality of this study is twofold: first, it investigates the varied attributes of urban parks and their associated negative emotions; second, it evaluates a range of internal and external elements related to negative emotions elicited by urban parks, including physical attributes, visual quality, accessibility, and park management.

The research focuses on two questions: (1) whether different parks lead to variations in the negative emotions expressed by the public, and if so, (2) what internal and external factors of urban parks contribute to these variations in negative emotions.

2.Literature Review

2.1. Impact of Urban Parks on the Public's Mental Health

A substantial body of research has concentrated on examining the beneficial effects of urban parks on the mental health of individuals. For example, Yuen and Jenkins (2020) explored how a visit to urban parks affected visitors' well-being. Using pre- and post-visit questionnaires, they found that park visits boosted visitors' mental health. In addition, accelerometers were used to track visitors' physical activity levels during their park visits. Jabbar et al. (2024) employed a questionnaire with 1050 respondents to assess the impact of urban green spaces on the mental health of residents in Lahore, Pakistan. The findings revealed a strongly positive relationship between urban green spaces and the promotion of human well-being.

The advent of big data has positioned the analysis and assessment of small blogs as a burgeoning area of academic interest (Naz et al., 2018). Scholars have collected data from social platforms such as Weibo, Twitter (X), and Facebook for sentiment and textual analysis in the field of landscape and urban planning (Kovacs-Györi et al., 2018; Fernandez et al., 2022; Huai et al., 2023). For example, Plunz et al. (2019) employed Twitter (X) data to assess the emotional states of visitors to parks in New York City, finding a positive association between park visits and the expression of positive emotions. Wang et al. (2021) assessed satisfaction with urban green spaces by leveraging social media content analysis and machine learning. They found a robust connection between urban park visits and the emotional well-being and satisfaction of those visitors. Kong et al. (2022) quantified visitors' positive emotions toward urban parks using social media data and sentiment analysis. They discovered variations in positive emotional levels among visitors to different types of urban parks and noted that positive emotions correlate positively with park size and the average size of water bodies, but negatively with large impervious surface areas.

Although the tools and technologies for examining the link between urban parks and visitors' mental health have advanced significantly, there has been a tendency to overlook the negative emotions of visitors. Negative emotions can more effectively reveal core issues in the landscape properties of urban parks, promoting more targeted improvements and offering tangible suggestions for enhancing the economic, social, and ecological benefits of urban parks. According to the Cannikin Law, this oversight may foster developments that only reinforce existing strengths rather than adequately addressing the weaknesses and areas that truly require intervention (Huai et al., 2023; Li et al., 2019).

2.2. Internal and External Aspects Affecting Negative Emotions in Urban Parks

Researchers have explored the relationship between various natural (normalized differential vegetation index [NDVI], restorability, etc.) and socio-economic (park management, cultural services, etc.) factors and the public's positive emotions elicited by urban parks. For instance, Cheng et al. (2021) applied the NDVI as the main independent variable to measure the green quality of urban parks. Natural indicators such as the proportion of impervious land, land surface temperature, and proportion of water were also frequently utilized in prior research. Wu et al. (2023) evaluated the impact of urban green space on environmental preferences, restorativeness, and other natural factors such as sound, air, and thermal environments on visitor emotions. In the socio-economic field, Chen et al. (2022) categorized parks into different levels (comprehensive park, specialized park, etc.) and measured the impact of park management on visitors' emotional perceptions. However, these studies tend to focus on a single aspect of natural or socio-economic factors, and there remains a deficiency in a comprehensive classification of the various factors that impact public emotions, especially those of a negative nature.

Therefore, we considered encompassing both internal and external factors of urban parks based on data listed in Table 1. The internal factors consisted of two major categories: physical attributes and landscape visual quality. Based on work by Wu et al. (2022), Kong et al. (2022), and Zhu et al. (2020), physical attributes include park size, perimeter, function mixing degree, road density, and crowdedness degree. In terms of landscape visual quality, we mainly used water size, land use, and vegetation coverage for measurement (Fan et al., 2021; Kong et al., 2022). In relation to the external factors, accessibility, built environment density and park management were used. The accessibility factors include public transportation accessibility and distance accessibility (Ding & Wang, 2024; Kong et al., 2022). In relation to built environment density, surrounding crowdedness degree and road density were utilized (Kong et al., 2022; Wu et al., 2022). In the realm of park management, we categorized the grade of parks in accordance with the "Nanjing Green Space System Planning (2013–2020)" (Chen et al., 2018). The Dianping App, an independent and nationwide-used third-party consumer review platform, was used to quantify public satisfaction with the parks (Liu & Xiao, 2020).

Table 1. Description of external and internal factors affecting negative sentiments

Classification	Field	Factor	Description	Value	Data Source	Reference
Internal factors	Physical attributes	Function mixing degree	The number of Points of Interest (POIs) of all facilities inside the park	Number of POIs per ha	POI data in Nanjing City (2024)	(Ding & Wang, 2024)
		Park perimeter	Perimeter of the park	Park perimeter (meter)	National Platform for Common GeoSpatial Information Services	(Cheng et al., 2021; Kong et al., 2022)
		Park type	Park types based on the Classification Standard for Urban Green Spaces	Four types of parks	CJJ_T_85-2017 Classification criteria for urban green space	(Ministry of Housing and Urban-Rural Development, PRC，2017)
		Park size	Park acreage	Park area (ha)	Nanjing Green Space System Planning (2013–2020)	(Chen et al., 2018; Zhu et al., 2020)
	Landscape visual quality	Land use	Impervious surface area	Impervious surface area (ha)	Based on 30m-resolution remote sensing data on land use in China in 2022	(Kong et al., 2022)
		Vegetation coverage	Normalized difference vegetation index (NDVI)	Rated from -1 to 1	Calculated from Landsat 8 in ENVI5.3	(Fan et al., 2021)
		Water feature size	Water area	Water area (ha)	Calculated from Landsat 8 in ENVI5.3	(Fan et al., 2021)
External factors	Accessibility	Distance accessibility	Distance from the park center point to the urban center	Distance from the park center point to the urban center (kilometer)	Calculated with Point Distance tool in ArcGIS 10.8	(Kong et al., 2022)
		Public transportation accessibility	Number of bus and subway stations surrounding the park	Number of bus and subway stations surrounding the park	Calculated with Point-in-Polygon tool in ArcGIS 10.8, within the 1000 m network zone	(Ding & Wang, 2024)
	Built environment density	Crowdedness degree	Average crowdedness around the urban park	Number of population around the park per ha	Calculated with the Field Calculator in ArcGIS 10.8, within the 500 m network zone	(Wu et al., 2022)
		Road density	Road density around the urban park	Length of roads around the park per ha	Calculated with the Line Density tool in ArcGIS 10.8, within the 500 m network zone	(Kong et al., 2022)
	Park management	Grade of park	Administrative management level of a park	Community park/district park/ city park	Nanjing Green Space System Planning (2013–2020)	(Chen et al., 2018)
		Tourist satisfaction	Public satisfaction from social media	Rated from 0 to 5	Dianping data (2022–2024)	(Liu & Xiao, 2020)

3. Methods

3.1. Study Area

Nanjing (north latitude 31°14 '~ 32°37', east longitude 118°22 '~ 119°14') is one of the important central cities in the Yangtze River Delta, China. As a key national scenic tourism city, it has a green coverage area of 103,423 hectares. With urban development, its ecological environment has encountered great challenges (Wan et al., 2024). The municipal government launched the *Measures for Urban Renewal of Nanjing* in 2023 (Nanjing.gov.com), which calls for "urban renewal carried out for damaged ecological environments, outdated supporting facilities, and low-service efficiency of urban mountains, green squares, urban parks, waterfront spaces, road and street alleys, etc." This regulation aims to improve urban green spaces and the public's well-being, offering valuable case studies for our examination of urban parks in Nanjing and the development of practical recommendations.

According to the planning scope formulated in "Nanjing Green Space System Planning (2013–2020)" and "Nanjing Urban Master Plan (2011–2020)," our research focuses on the main districts, including Gulou, Qinhuai, Xuanwu, Jianye, Yuhuatai, and Qixia. The high population density and rich types of parks in the main districts of Nanjing enhance the accuracy and feasibility of data collection. Based on the "List of Nanjing City Parks" provided by the Nanjing Greening and Landscaping Bureau, there are 101 urban parks in the research area, encompassing four types of parks: comprehensive, ecological, community, and archaeological. From the listed parks, the data for 18 were unavailable (data for 12 could not be obtained from Weibo, and six lacked sentiment analysis results due to skewed emotional expressions). Therefore, this research only focuses on the remaining 83 parks in the Nanjing main districts.

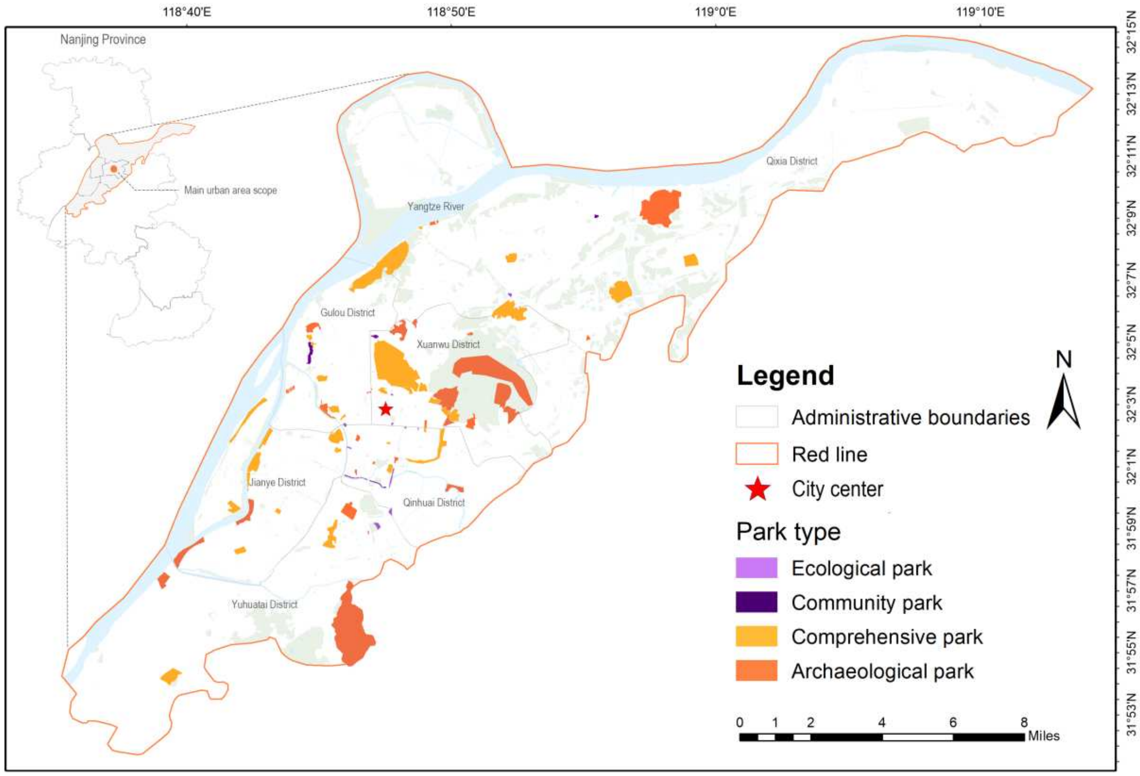

Figure 1. Map of park types and distribution in the Nanjing main districts.

3.2. Overall Design

This study analyzed public negative emotions and their influencing factors for 83 urban parks in Nanjing's main districts through the following steps: First, Python was used to crawl Weibo posts and comments from 2018 to 2023, with 13,838 valid entries retained after data cleaning. Next, sentiment analysis was conducted using the Dalian University of Technology Emotion Ontology Database Dictionary (hereafter referred to as "DUT Emotion Dictionary"), and results were cross-validated via Baidu API and manual annotation. The Negative Emotion Index (NEI) (Cheng et al., 2021) was then calculated to quantify emotional intensity for each park. Finally, one-way ANOVA was used to examine whether differences existed among different parks (RQ1). Stepwise multiple linear regression was employed to examine the relationship between park attributes (seven internal factors and six external factors) and negative emotions (RQ2), with standardized regression coefficients (β) assessing each factor's effect strength and direction. Finally, implications for theory and practice were proposed (Figure 3).

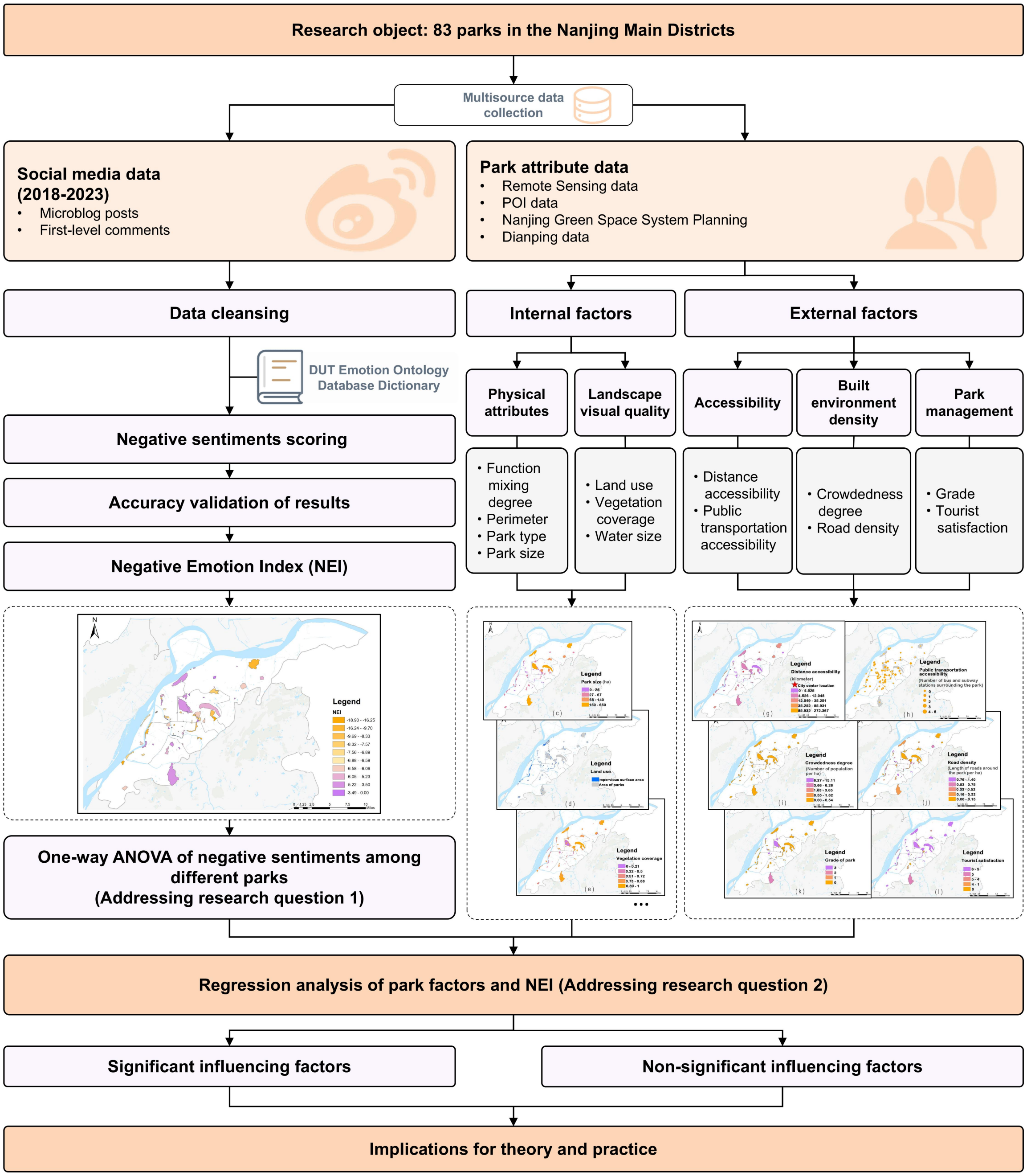

Figure 3. Research design.

3.3. Data Collection

Social media networks provide valuable resources for collecting data and obtaining users' perceptions (Park et al., 2020). As the largest social media website in China, Sina Weibo had 511 million monthly active users and 224 million daily active users as of September 2020 (Weibo data center, 2020). To capture the current park status with sufficient data, data from the past five years, from January 2018 to January 2023, was analyzed. The chosen time span evenly covers pre-pandemic, pandemic, and post-pandemic periods to avoid bias from any specific phase. Python was used to crawl microblog posts and first-level comments from the public related to 83 parks in Nanjing main districts. The specific operation process was as follows: (1) Simulate login. The Weibo Uniform Resource Locator (https://weibo.com/) was used to access the Weibo interface, where a username and password were entered to simulate the login process, and the corresponding cookie information was obtained. (2) Keyword search. The name of each park was entered as a search keyword after the mock login, ensuring that the collected data were highly relevant to the research topic (Cao et al., 2016). (3) Data collection. The data from all retrieved posts were collected, including microblog username, user ID, post content, number of likes, number of forwards, number of comments, posting location, and IP address. (4) Data storage. Once the data collection process was finalized and the accuracy of the information was confirmed within the designated time frame, the gathered data were exported and securely stored.

3.4. Quantifying Negative Public Emotions

The initial dataset comprised 55,896 microblog entries that underwent comprehensive data cleansing, resulting in 13,838 valid entries. The cleansing process involved removing duplicate and repeated microblog posts, filtering out content unrelated to the landscape features of urban parks, and excluding official government communications that represent promotional content rather than public emotional expression.

As a fundamental natural language processing (NLP) technique, sentiment analysis examines subjective textual information to determine emotional polarity (positive, neutral, or negative) and calculates corresponding probability scores (Whitelaw et al., 2005). In this study, sentiment analysis was conducted based on the DUT Emotion Dictionary (Deng, 2020), a recognized standard for sentiment analysis in Chinese language contexts (Cao et al., 2016; Yao et al., 2021). Through this analytical framework, we derived intensity-based sentiment indices that effectively captured and classified emotional dispositions toward urban parks across Nanjing's main districts (Zheng et al., 2019).

3.5. Verifying the Results of the Sentiment Analysis

Multimethod mutual verification and manual sampling inspection are widely recognized as essential for enhancing the validity and reliability of sentiment analysis results (Boiy & Moens, 2009; Mohammad & Turney, 2013). To validate the sentiment analysis results based on the DUT Emotion Dictionary, two levels of verification were conducted using the Baidu API (one of the popular NLP models used in Chinese contexts) and manual annotations: (1) validation of sentiment polarity accuracy, and (2) validation of sentiment intensity.

Specifically, a random selection of 1000 Weibo posts were retrieved from the initial dataset, accounting for around 10% of the total datasets. These posts were manually annotated and cross-checked by three trained researchers, categorizing each post as negative, neutral, or positive based on contextual emotional expression. Then, the sentiment labels derived from the DUT Emotion Dictionary (recategorized by polarity) were compared against manual annotations by a Spearman's rank correlation analysis. The findings revealed a strong agreement (correlation rho = 0.791, $p < 0.001$), confirming high accuracy in sentiment polarity classification. Further, to validate the consistency of sentiment intensity, sentiment analysis was performed using the Baidu API. A Pearson's correlation analysis was conducted to compare the sentiment analysis results from the Baidu API with the sentiment scores derived from the DUT Emotion Dictionary analysis. The correlation coefficient between the two variables was 0.892, thereby affirming the accuracy of the sentiment intensity.

3.6. Exploring the Relationship Between Public Negative Emotions and Urban Park Attributes

To ensure comparability across the 83 parks, we normalized the negative emotion scores of each individual comment using the NEI (Cheng et al., 2021). The NEI represents the average of all negative emotion scores for a given park. All NEI values are negative, where larger absolute values indicate higher likelihood of eliciting negative emotions, while smaller absolute values suggest lower likelihood.

$$\mathrm{NEI_i} = \frac{\sum_{j=1}^{n_i} s_{ij}}{n}$$

where NEI_i is the Negative Emotion Index for park (i); n_i is the total number of comments for park (i); and s_{ij} is the negative emotion score of the j-th comment for park (i).

A one-way ANOVA was conducted to examine if there are significant differences in the negative sentiment toward 83 parks expressed by the public. A comprehensive set of internal and external indicators was employed to evaluate the impact of various factors on urban parks. Referring to Table 1, these indicators include seven internal factors, namely park type, park size, land use, perimeter, function mixing degree, vegetation coverage, and water feature size (Chen et al., 2021). Additionally, there are six external factors, including distance accessibility, road density, public transportation accessibility, crowdedness degree, tourist satisfaction, and grade (Ding & Wang, 2024; Lyu & Zhang, 2019).

3.6.1. Internal Factors

As shown in Figure 4, land use, water feature size and vegetation coverage were employed to characterize the landscape visual quality of the urban parks. Water feature size was calculated using a geographical information system (GIS) and remote sensing imagery techniques and was expressed in hectares (ha). Additionally, we incorporated the Normalized Difference Vegetation Index (NDVI), computed using image processing software, such as ENVI 5.3, as a proxy for vegetation coverage (Fan et al., 2021). The coverage of NDVI was calculated within a designated area (landsat8) within the urban parks, which, alongside water metrics, served as comprehensive indicators reflecting the visual quality and ecological vitality of the parks. Land use, represented by the area of impervious surfaces, was analyzed through 30m-resolution Landsat imagery to assess urban land cover characteristics (Kong et al., 2022).

The physical attributes include function mixing degree, park perimeter, type, and size. The function mixing degree was calculated as the total number of points of interest (POIs) divided by the park area. Park perimeter (m) was derived from boundary shapefiles obtained via the National Platform for Common GeoSpatial Information Services (Cheng et al., 2021; Kong et al., 2022) and calculated via the calculate geometry tool in ArcGIS 10.8. Park size (ha) was sourced from the Nanjing Green Space System Planning (2013–2020) (Chen et al., 2018; Zhu et al., 2020). Boundary polygons were processed in ArcGIS 10.8, with area computed in hectare (ha).

Park type was also recognized as an integral intrinsic attribute of the parks, as different types of parks often serve distinct functions and display various landscape features (Kong et al., 2022). In our research, the parks were classified into community parks, archaeological parks, comprehensive parks, and ecological parks, based on the classification standard for urban green spaces issued by the Ministry of Housing and Urban–Rural Development of the People's Republic of China (2017). Community parks are independent parks equipped with fundamental recreational amenities, catering to residents within a specific neighborhood for daily leisure. Archaeological parks, dedicated to preserving and interpreting archaeological sites and artifacts, play a crucial role in conserving cultural heritage and educating the public. Comprehensive parks are characterized by diverse offerings and suitability for a wide range of outdoor activities, providing comprehensive recreational services. Ecological parks focus on forest ecotourism and natural landscape tours, featuring extensive woodland areas.

3.6.2. External Factors

Accessibility serves as a prevalent metric in studies pertaining to urban green spaces. Researchers have underscored the benefits of the 15-minute living circle in fostering sustainable development and increasing urban vitality (Zhang et al., 2022). Various urban planning guidelines, along with the World Health Organization (WHO), consider a 10- to 15-minute walking distance—equating to roughly 1,000 meters—as a standard for accessible urban services (Burke et al., 2022; WHO, 2016). This distance effectively captures the typical distance that individuals are willing to walk to access public facilities. Consequently, the number of bus and subway stations located within the 1,000-meter buffer zones surrounding the main entrances of parks has been used as a proxy for public transportation accessibility. Utilizing ArcGIS 10.8, the buffer tool was applied to create a 1,000-meter radial zone around each park's main access points. Then, the point-in-polygon tool was used to identify and count the transit nodes (bus and subway stations) falling within these defined buffer areas (Bernabeu-Bautista et al., 2023). Moreover, the distance accessibility was measured by the distance from the park's main entrances to the city center—Xinjiekou area in Nanjing (Figure 4).

For built environment density analysis, a 500-meter buffer was employed, aligning with evidence that this scale optimally captures the built environment's impacts on park perception and mental health (Lyu & Zhang, 2019; Zhang et al., 2022). Therefore, the road density around each urban park was calculated as the total length of the roads within a 500-

meter buffer zone around the park divided by the area of this zone (Lyu & Zhang, 2019). This calculation was performed using the line density measurement tool in ArcGIS 10.8. Similarly, crowdedness degree derives from Nanjing's population density data clipped to 500m buffers, calculated per unit area via field calculator (Kong et al., 2022) (Figure 4).

For park management, grade of park was determined based on official classifications provided in the Nanjing Green Space System Planning (2013–2020) (Chen et al., 2018). Parks were categorized into community parks, district parks, and city parks. Tourist satisfaction was assessed based on user ratings from the Dianping platform (2022–2024), a major Chinese review site for public venues. Each park was assigned an average satisfaction score ranging from 0 to 5, reflecting public evaluations.

3.7. Statistical Analysis

A one-way ANOVA was used to verify whether significant differences existed in the negative emotions toward different parks. Then, stepwise multiple linear regression models were used to analyze the correlation between the public's negative emotions and the urban parks' attributes. Following Field (2013), the backward method was applied to construct an optimal predictive model, beginning with a full model containing all candidate independent variables and iteratively removing those with insignificant effects on the dependent variable. This process eliminated predictors failing to meet the $p < 0.05$ significance threshold, ultimately yielding a parsimonious model with enhanced accuracy. Result interpretation relied on standardized regression coefficients (β), as β values allowed for direct cross-variable comparison by eliminating unit differences through standardization. The absolute magnitude |β| quantified each predictor's influence strength, while the sign indicated directionality. Negative coefficients ($\beta < 0$) signified that higher attribute values intensified the negative sentiments, whereas positive coefficients ($\beta > 0$) indicated mitigating effects on the sentiments (Fu et al., 2023).

4. Results

4.1. Differences in Negative Emotions Concerning Urban Parks

A one-way ANOVA was performed to monitor the presence of significant differences in the public's expressed negative emotions toward different urban parks. Normality checks and Levene's test were carried out, and the assumptions were met. A significant difference was found in the mean negative emotions of 83 urban parks ($F = 6.730$, $p < 0.001$). As shown in Figure 3, the natural breaks method in ArcGIS was used to categorize the different Negative Emotion Index (NEI) values of the 83 parks into 10 grades. The NEI ranged from −18.90 to 0, with an average of −6.03 and a standard deviation (SD) of 3.65. Zhongshan Sports Park and Sanqiao Wetland Park generated the most negative emotions, with NEI values of −18.90 and −16.25, respectively. The NEIs of nine parks in total were lower than −10, while most parks ranged from −3.50 to −9.70. Fourteen parks had no negative posts, resulting in an NEI equal to 0.

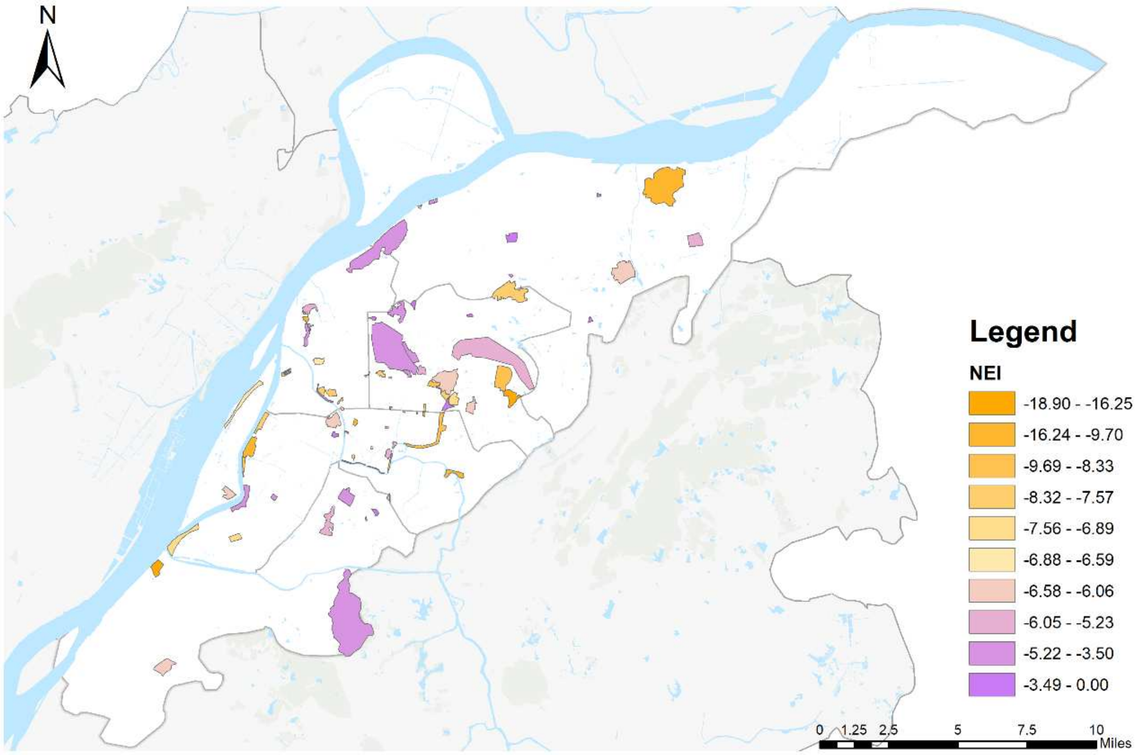

Figure 3. Negative Emotion Index (NEI) distribution of different urban parks in Nanjing's main districts.

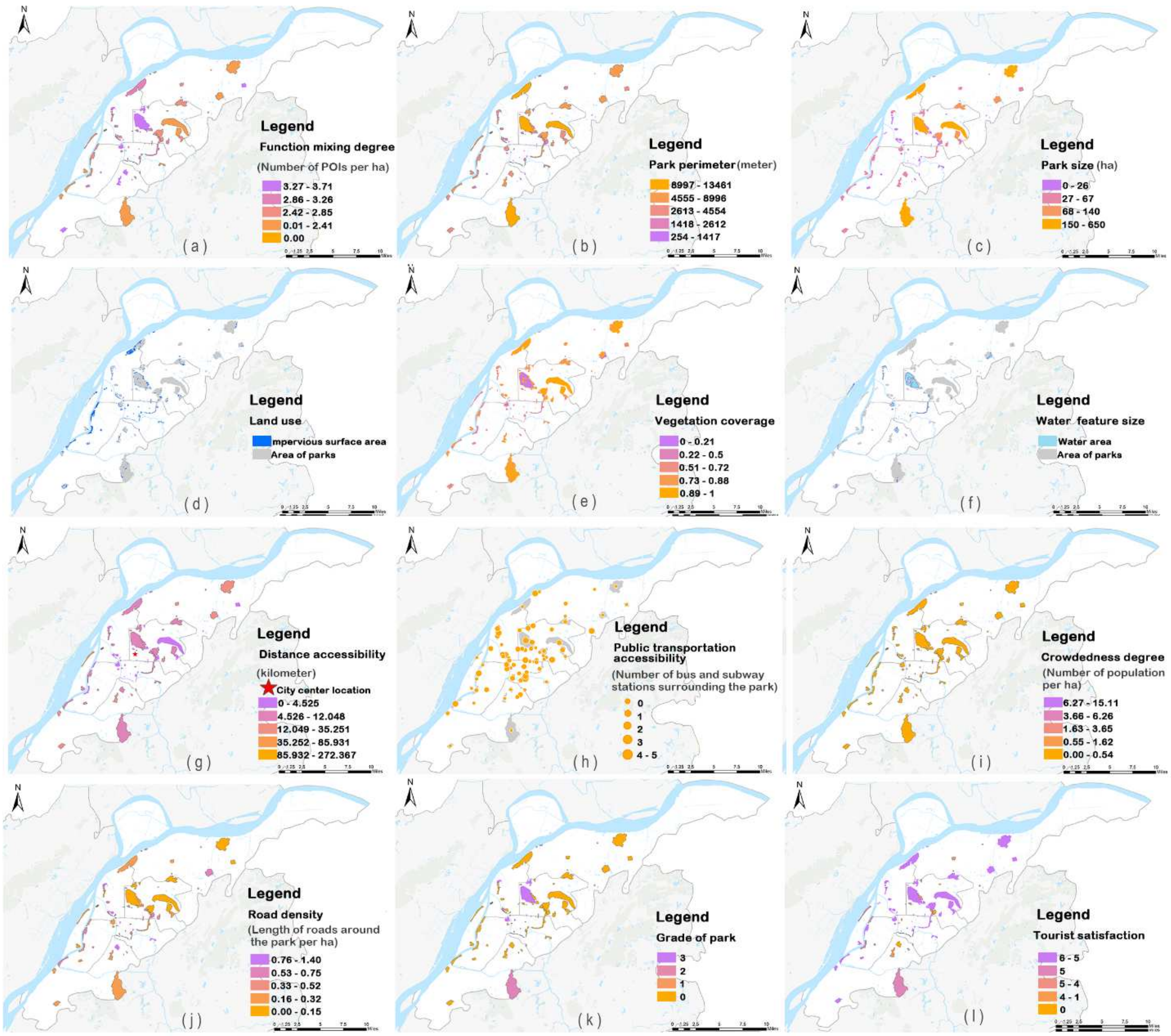

Figure 4. Attributes of urban parks in Nanjing's main districts: (a) function mixing degree, (b) park perimeter, (c) park size, (d) land use, (e) vegetation coverage, (f) water feature size, (g) distance accessibility, (h) public transportation accessibility, (i) crowdedness degree, (j) road density, (k) grade of park, and (l) tourist satisfaction.

4.2. Relationship between Public Negative Emotions and Park Attributes

A multiple linear regression analysis employing a backward stepwise method was utilized to identify the factors that affected the NEI. The adjusted R-squared value for these models was 0.994, indicating that the models explained 99.4% of the variability in the negative emotional changes attributed to the influencing factors. Additionally, the standard error of the estimates was only 0.309, and the multiple linear regression passed the F test with $p < 0.01$, indicating that at least one of the independent variables successfully accounted for a portion of the variation observed in the dependent variable, thereby establishing a valid model.

The results of the multiple linear regression are shown in Table 2. Thirteen factors were assessed and categorized into two elements: seven internal factors and six external factors. The results showed that 12 factors of these were significantly correlated with the NEI; however, the grade of the parks did not show a significant correlation, while park type displayed selective influences. In particular, among the three park types compared to comprehensive parks (the reference group), only community parks exhibited a statistically significant variation in public perception, whereas the other two types (ecological and archaeological parks) did not demonstrate statistically significant effects.

Among the significantly correlated attributes, five were negatively correlated, indicating that the higher these indicators were, the more negative visitors' sentiments toward the park became. Standardized regression coefficients (β) indicated the extent of the influence, with road density and land use representing the strongest negative drivers, followed by park area, park type (i.e., community park vs. comprehensive park), and distance accessibility. Similarly, seven indicators were positively correlated, meaning that higher levels of these attributes contributed to fewer negative sentiments from visitors. Among these, water feature size and crowdedness degree dominated a wider portion of the positive effects, outperforming vegetation coverage, function mixing degree, tourist satisfaction, and public transport accessibility.

Table 2. Correlation between internal and external factors and the Negative Emotion Index

Category	Attribute	Unstandardized regression coefficient		Standardized regression coefficient	Significance
		B	Standard error	β	
Internal factors	Community park	−2.984	0.452	−0.178	0.001*
	Park size	−7.725E-6	0.000	−0.222	0.013*
	Park perimeter	0.002	0.000	0.409	0.004*
	Water feature size	12.894	0.517	1.054	<0.001**
	Vegetation coverage	19.655	0.937	0.706	<0.001**
	Land use	−8.368E-5	0.000	−0.570	<0.001**
	Function mixing degree	0.791	0.043	0.643	<0.001**
External factors	Public transportation accessibility	1.113	0.164	0.271	0.001*
	Distance accessibility	−1.089E-5	0.000	−0.172	0.002*
	Road density	−12.847	0.512	−1.087	<0.001**
	Crowdedness degree	0.780	0.032	0.789	<0.001**
	Tourist satisfaction	6.791	0.369	0.499	<0.001**

Note: $^{**}p < 0.05$, $^{***}p < 0.01$

The factors with the highest absolute values of the standardized coefficients (β) exhibited the most influential effects on public sentiment. Road density (β = −1.087) exerted the strongest negative effect on public sentiment, where each 1 kilometer/hectare increase in road density within the 500-meter buffer caused a 12.847-point NEI decline. Conversely, water area (β = 1.054) provided the most substantial positive influence on public sentiment, with each additional hectare of water increasing the NEI by 12.894 points.

The factors exhibiting the lowest absolute values of the standardized coefficients (β) in comparison to other factors indicated practically negligible effects on public sentiment. Distance accessibility (β = −0.172, B = -1.089×10^{-5} per km) and park area (β = −0.222, B = -7.725×10^{-6} per ha) showed statistically significant yet practically negligible impacts (e.g., a 100-hectare park expansion reduced the NEI by only 0.00077 points). Additionally, the community parks produced an NEI that was 2.984 points lower than that of the other park types, reflecting a greater level of negative sentiment among the public toward the community parks. Conversely, no statistically significant variations in the NEI were observed in the archaeological and ecological parks compared to the comprehensive parks, suggesting a relative parity in the public's negative emotions across these park types.

5. Discussion

5.1. Distribution of Parks with Different Levels of Negative Emotions

The 83 parks, situated in diverse locations throughout the central urban area of Nanjing, represent various park types and were established at different times. Consequently, their internal and external features, along with the outcomes of the sentiment analysis, demonstrate a significant range of diversity. In terms of the NEI, the parks with higher scores are predominantly concentrated in the Xuanwu and Qinhuai districts (see Figure 2). This may be attributed to the majority of the parks in these areas functioning as scenic spots; thus, they receive superior management and maintenance. Furthermore, these districts are primarily characterized by built environments that represent the historic urban landscape of Nanjing, rendering their overall external characteristics less susceptible to eliciting negative emotional responses (Liang et al., 2022).

Additionally, several parks with elevated NEI scores are dispersed in proximity to Nanjing's urban–rural fringe. This could be attributed to the generally superior natural landscapes adjacent to these parks and the higher quality of blue-green spaces they offer (Li et al., 2023; Wang et al., 2016). For instance, the parks situated alongside the Yangtze River tended to exhibit relatively higher NEI scores. In contrast, parks in the city center seem to show more signs of negative effects. This situation necessitates a deeper investigation into the factors that could influence public negative emotions.

5.2. Relationship between Public Negative Sentiments and Park Attributes

5.2.1. Internal Factors

The impact of internal factors within the parks on the public's negative emotions could be attributed to the varying configurations of these spaces. Factors such as park size, water feature size, land use, and vegetation coverage differ in terms of their psychological restoration capacities. These factors influence public sentiment through multiple sensory modalities (Castañeda et al., 2024; Chen & Yuan, 2020; Tsurumi et al., 2024).

Many researchers have suggested that the natural environments of parks relieve stress and restore attentional levels (Wang et al., 2016; Yang et al., 2025). Specifically, water elements and greenery significantly enhance physiological and psychological recovery (Zhang et al., 2023). For example, Jin et al. (2024) found that blue spaces (water features) are most effective at relieving stress, followed by open green spaces, while grey spaces (hard covered areas) show poor recovery efficiency, as indicated by continuous monitoring of changes. This pattern holds across cultures: Studies in Tokyo and Copenhagen have reported that parks with prominent water features and dense greenery are linked to reduced stress and enhanced emotional well-being (Astell-Burt & Feng, 2019; Tsurumi et al., 2024). Thus, visiting parks with different spatial configurations affects mental restoration, which in turn shapes public sentiment.

In contrast to previous studies, which show that larger parks are generally more conducive to the presence of attention restoration elements (Kong et al., 2022), our results showed that park size had a negative effect on public sentiment. This finding contrasts with evidence from Western contexts, particularly North America, where larger urban parks tend to correlate with better mental health outcomes due to factors such as enhanced opportunities for solitude, recreation, and perceived safety (Giles-Corti et al., 2005). The discrepancy may be attributed to contextual differences in park design and urban environments. In China, large parks may reduce benefits related to vegetation and water coverage (Wang et al., 2024) and may instead introduce challenges, such as reduced subjective safety and diminished public transportation accessibility (Park et al., 2021; Yang et al., 2023).

The absolute value of the NEI was highest for the community parks, whereas no statistically significant disparities were observed among the other three park types. This pattern may stem from the distinct functions and designs of different parks, which shape visitor experiences and the intensity of negative emotions through factors such as size, water features, greenery, accessibility, and crowding. Community parks, often small in size and lacking in natural elements, mainly focus on providing fundamental fitness and recreational facilities. They are also more susceptible to noise (Yang et al., 2024), which can greatly impact visitors' experiences and feelings (Yin et al., 2023). In comparison, comprehensive parks are likely to have a higher quality of natural environment and varied services, which may reduce negative emotions (Nigg et al., 2024). Our findings align with studies from Seoul and Santiago, where smaller neighborhood parks frequently suffered from insufficient biodiversity and poor amenities, leading to lower user satisfaction (De la Barrera, 2019; Heo et al, 2021). Collectively, these results underscore that across diverse cultural contexts, the ecological quality and design sophistication of small-scale community parks play a pivotal role in influencing emotional well-being.

5.2.2. External Factors

The results showed that distance accessibility was negatively correlated with the NEI and that public transportation accessibility was positively correlated with the NEI. As with our findings, previous research identified public transportation accessibility as the key factor controlling blue-green space vitality, which was associated with fewer negative emotions (Shao & Chung, 2024). Crowdedness degree was positively correlated with the NEI. The tendency for individuals to express more negative sentiments toward parks located in areas with lower population densities can be partially attributed to the limited variety of nearby recreational amenities (Cheng et al., 2021; Xu et al., 2024). Meanwhile, the interaction between pedestrian accessibility and crowdedness degree is significant; together, they affect blue-green space vitality. Areas with a high crowdedness degree tend to have better walkability, and areas with better walkability are more likely to attract people to live there, thus forming a virtuous cycle and enhancing the vitality of the blue-green spaces (Ding & Wang, 2024).

In line with prior studies (Lyu & Zhang, 2019), an increase in road density was found to be associated with a greater likelihood of citizens experiencing negative emotions. One reason for this may be that the high density of the road network may lead to increased traffic noise and air pollution, thus increasing the negative mood of the public (Zhao et al., 2025). Empirical evidence from major global cities, including London and Los Angeles, substantiates this mechanism, demonstrating how proximate traffic exposure can significantly diminish the psychological benefits typically derived from urban green spaces (Gidlow et al., 2016; Van den Bosch & Sang, 2017).

Contrasting with previous studies, the grades of the parks were not significantly correlated with the NEI. This may be because park management constitutes a multidimensional and intricate system. The grade of a park is likely driven more by the administrative needs of governmental departments rather than factors indicating landscape quality. Furthermore, the effectiveness of park management characterized by the grade of the park may exhibit a time lag, meaning that current management measures may take some time to impact visitor emotions. This lag effect may result in an insignificant correlation between management measures and visitor emotions in the short term.

Notably, while park grade showed no significant relationship, tourist satisfaction demonstrated a consistent positive association with NEI values. This contrast reinforces the validity of our sentiment analysis methodology while highlighting the differential responsiveness of emotional indicators to various park quality dimensions.

5.3. Implications for Theory and Practice

This research builds upon earlier investigations into the relationship between urban green spaces and mental health, shifting the focus from positive emotional outcomes to negative reactions to address planning and management challenges more effectively. Expanding on prior research, it provides a theoretical framework that integrates the internal and external characteristics of urban parks to investigate the factors that influence negative emotional responses. The internal features focus on physical attributes and visual quality; the external features integrate accessibility, built-environment density and park management. This multidimensional evaluation system will benefit user perception and green space evaluation studies in the planning discipline.

Furthermore, the research findings have implications for policymakers engaged in urban renewal initiatives in that such initiatives should be prioritized by examining the attributes associated with higher absolute NEI values. Park management requires a comprehensive approach addressing both external factors (regulating built-environment density and accessibility) and internal factors. Internally, managers should maintain critical natural features - particularly water bodies and vegetation - that significantly influence emotional responses. Community parks, while vital for urban services and resident well-being (Shao & Lu, 2024), were most likely to elicit negative emotions among the four park types examined. Therefore, renovation and optimization of these parks should be prioritized in Nanjing.

As for landscape and urban planning practitioners, the relationship between different park attributes and the NEI helps to support the composition and configuration of urban parks and their surroundings. Road density exerts the most significant influence on NEI values, likely due to associated noise, pollution, and reduced pedestrian safety. Designers can mitigate this by incorporating green buffers, such as dense tree plantings, earthen berms, or sound-absorbing planting schemes along park peripheries. Internal factors, including water feature size and vegetation coverage, have substantial impacts on the NEI. Thus, increasing the visibility and accessibility of water features, such as ponds, fountains, and wetland zones, can foster psychological restoration. Similarly, improving vegetation coverage through diverse and layered planting can help reduce stress and improve thermal comfort. Moreover, parks with longer perimeters and higher function mixing degrees are associated with reduced negativity. This suggests that spatial configurations promoting varied and engaging park edges can enhance user satisfaction through meandering trails, landscape transitions, and multifunctional zones.

5.4. Weaknesses and Biases in Social Media Data

While this study utilizes a large dataset derived from Weibo posts to assess the public's negative sentiments toward urban parks, several inherent limitations and potential biases associated with social media data warrant discussion. First, social media users, often younger and more educated, may not represent the general population. This can skew public sentiment representation and limit the accuracy of Weibo-based park-use analysis in reflecting total urban park usage (Zhang & Zhou, 2018). Thus, the sentiments expressed on social media may not represent the entire population, particularly less privileged or less active users. Second, as highlighted in the introduction, the content of social media posts may not accurately reflect the true sentiment of the public. Users may have different motivations for posting on social media, such as the desire for attention or the inclination to voice extreme viewpoints, which can lead to data distortion (Lopez et al., 2019). Lastly, the spatial and temporal coverage of social media data may be uneven. Certain areas or periods may exhibit higher social media activities than others; this imbalance may introduce analytical biases. Therefore, conducting small-scale surveys and comparative validation is essential to ensure the representativeness of the data (Ye & Qiu, 2021).

6. Conclusion

This research investigated the internal and external factors of urban parks that influence the negative emotions expressed by the public in Nanjing's main districts. An integrated approach combining social media analysis with spatial metrics was employed to evaluate the impact of various park characteristics on visitors' expressed negative emotions. The results revealed significant relationships between different external and internal factors and the negative sentiments reported by the public. Specifically, road density, park size, and land use correlated with increased negative emotions, while factors such as increased public transportation accessibility, crowdedness degree, function mixing degree, park perimeter, vegetation coverage, tourist satisfaction, and water feature size helped reduce negative emotions. Furthermore, the community parks tended to have higher negative emotion levels than the comprehensive parks. Among these factors, the most impactful factors on negative sentiments were road density and water size, followed by vegetation coverage and crowdedness degree. The findings highlight the significant impact of urban park attributes on emotional well-being, offering actionable insights for urban planning and park management.

The limitations of this research mainly lie in three areas. First, Weibo data suffers from representative bias, as its user base (predominantly younger, highly educated, and from privileged backgrounds) and content (influenced by posting motivations) may fail to reflect genuine public sentiment. Second, this study did not control for temporal factors (e.g., seasonality and weather), despite previous studies indicating that park-related sentiments can significantly fluctuate due to variations in temperature, sunlight, and air quality (Knez & Thorsson, 2006; Maas et al., 2009). As our multiyear dataset lacked temporal stratification, this could have introduced unmeasured variations in the emotional responses. Future work should incorporate these controls to enhance sentiment analysis accuracy. Third, this research focused on cases in Nanjing; future research can examine variations and similarities in the public's perceptions of urban parks across different urban regions and cultural contexts to derive more generalized insights.

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