PERCEPTION AND REALITY: URBAN GREEN SPACE ANALYSIS USING LANGUAGE MODEL-BASED SOCIAL MEDIA INSIGHTS

A Case Study within Shanghai's Inner Ring

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Abstract. As urbanization accelerates, urban green spaces play an increasingly integral role in daily life. The development of large language models (LLM) provides a practical method for assessing how people perceive green spaces. This study employs prompt-turning techniques to analyze social media data, aiming to uncover public sentiments and correlate them with the actual conditions of urban green spaces. By categorizing evaluative dimensions — location, landscape quality, facility levels, and management — diverse areas of public focus are revealed. We utilize both dictionary-based and language model-based methods for the analysis of overall emotional perception and dimensional emotional perception. Classification of sentiments into positive, neutral, and negative categories enhances our understanding of the public's general emotional inclinations. Using various spatial analysis techniques, the study delves into the current conditions of green spaces across these evaluative dimensions. In conclusion, a correlation analysis exposes patterns and disparities in these evaluative dimensions, providing valuable insights into understanding public emotional tendencies and offering effective recommendations from the perspective of public perception.

Keywords. Urban green spaces, Social media analysis, Public Sentiment, Spatial analysis, Prompt-turning.

1. Introduction

As global urbanization progresses, the impact of urban environments on residents' physical and mental health, including issues like depression and anxiety, has been confirmed (Helbich et al., 2019). Urban green spaces are considered not only to alleviate these issues but also to bring social and economic benefits to cities (Fam et al., 2008). According to China's land classification, park green spaces, as one type of urban green space system, play a crucial role by providing recreational and relaxing

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areas for people.

The study of Green Space Satisfaction (GSS) emerged from the direct relationship between residents' practical perceptions and the actual conditions of green spaces (Gozalo et al., 2018; Kuldna et al., 2020). Conventional approaches to gathering perceptions, like surveys and field observations, have drawbacks like exorbitant research expenses and restrictions on the temporal and spatial scales of their application. The emergence of multi-source data and technology has made social media—which includes text and images—an essential source of data for researching people's perceptions of green spaces (Cui et al., 2021; Grzyb et al., 2021).

Among these data, text data, due to its rich information content, has become an essential component of green space perception studies using natural language processing methods. Two primary approaches are employed in the perception analysis of text data. One approach relies on dictionary-based methods, utilizing software like RostCM6 and Ucinet6 for sentiment analysis to capture social media users' emotional tendencies. Although the usage limit is lower for this approach, generalizability is restricted because it requires high-quality domain-specific dictionaries and sentiment dictionaries as supplements. Studies have already been done on the automatic translation of Chinese to English to create a lexicon of emotions in Chinese (Xu et al., 2013). Another strategy makes use of deep learning techniques, including both supervised and semi-supervised learning. However, traditional machine learning-based techniques usually involve laborious manual labeling and refer to a large volume of annotated data, such as Support Vector Machines (SVM) and KNN (Huq et al., 2017). These approaches have limitations when it comes to analyzing data that has never been seen before because they need time for dictionary or model training in the beginning.

Large language model development (Zhao et al., 2023) has currently lowered operating costs and exhibited a remarkable ability for unsupervised learning, making prompt-turning techniques (Liu et al., 2021) applicable to a range of downstream tasks, such as sentiment analysis of perceptions of green spaces. This method is more operationally viable than traditional approaches because it can potentially achieve classification and sentiment evaluation of previously unseen text data by varying the prompt words.

2. Research Design

2.1. RESEARCH FRAMEWORK

To explore the correlation between social media sentiment and the actual conditions of park green spaces, we initially synthesized relevant studies, identifying four perceptual elements influencing park perceptions: location, landscape quality, facility levels, and management (Reyes-Riveros et al., 2021; van Dinter et al., 2022). Subsequently, Dianping (http://www.dianping.com), a well-known Chinese online consumer review and lifestyle service platform, was chosen as our data collection platform. It provides a large dataset for sentiment analysis of social media data related to the research sites all year long. Following that, a large-scale model was used to categorize social media comments according to the evaluative components involved.

This allowed for a perception analysis to be conducted across multiple dimensions in the social media data. On the other hand, concerning the mentioned dimensions, this study conducted an analysis of the actual conditions of urban green spaces using multi-sources data, including built environment data, Points of Interest (POI) data, street view data, and others. Finally, a comparative analysis was used to examine the relationship between the two sets of data, which helped to clarify the relationship between urban green spaces and public perceptions.

2.2. STUDY AREA

The research sites are situated within Shanghai's inner ring and are accessible to the public without charge. Each selected urban park spans over 100,000 square meters, accumulating over 4000 reviews on Dianping. These parks include People's Park, Zhongshan Park, North Bund Riverside Green Space, and Century Park (Figure 1).

This study's area encompasses both the internal area and the influence area. The measurement of landscape quality dimensions focuses on the internal areas of the park, while location and service facility dimensions take into account the radiating effects in the surrounding areas, utilizing the chosen radius within influence area. The research focuses on urban parks, in accordance with the "14th Five-Year Plan for the Construction of Ecological Space and the Optimization of Urban Environment in Shanghai", and determines that the influence and service range of green spaces in central urban parks on the surrounding environment extend to 500 meters.

Figure 1. Study area

2.3. SOCIAL MEDIA TEXT ANALYSIS

2.3.1. Data collection

For the chosen research sites in this study, data from Dianping were gathered between November 1, 2022, and October 31, 2023. A total of 4290 reviews were collected from four different research areas, encompassing information such as park names, user IDs, ratings, comment texts, and evaluation timestamps.

Preliminary processing of the comment texts was conducted, which included operations such as data deduplication and the removal of unnecessary text. Subsequently, regular expressions were employed to eliminate invalid information and emoticons.

2.3.2. Sentence Segmentation and Perceptual dimension classification

The text data processing is shown in Figure 2. Given that comment sentences are often lengthy and involve assessments of various dimensions, a segmentation process was implemented. Initially, the evaluative text underwent sentence segmentation and word tokenization. Subsequently, classification was conducted using the API of ChatGPT-3.5, with a relatively high temperature setting. Through adjustments of the prompt iterations, each segmented sentence was categorized into one of four classes: location, landscape quality, facility levels, and management. Sentences that could not be classified into these four groups were designated as undistinguished.

2.3.3. Sentiments analysis

Sentiment analysis comprised two components: overall emotional perception and dimensional emotional perception. In this process, two evaluation methods were employed: the dictionary-based method and the large language model-based method. In the dictionary-based method, word segmentation was initially performed using RSTCM6, followed by sentiment analysis utilizing an internal emotion dictionary. This resulted in a language orientation score ranging from -100 to 100, where positive values indicated a positive emotion, and negative values denoted a negative emotion. The language model-based method employed the natural language processing capabilities of Baidu Intelligent Cloud, whose training corpus was primarily in Chinese, providing good understanding and generalization abilities in Chinese. This platform could determine the sentiment polarity category (positive, negative, neutral) of a sentence and provide the corresponding confidence level.

For overall emotional perception, the evaluation outcomes of both analysis methods were calibrated using the rating scores (typically considered negative if the score was below 3.5 out of a total of 5). Concerning dimensional evaluations, a comparative analysis was conducted with the indicators of each dimension that measured the status of green spaces.

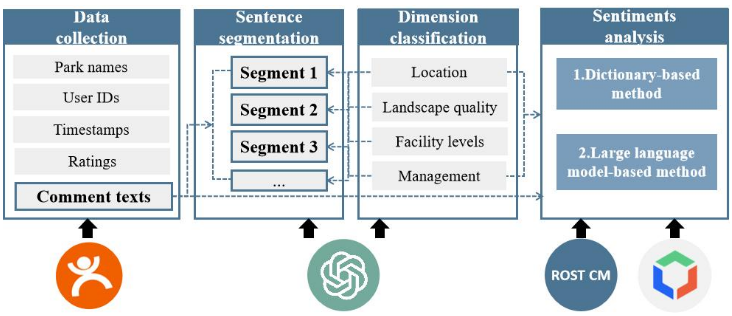

Figure 2. Text data processing

2.4. MEARSURING OF GREEN SPACE STATUS

2.4.1. Data collection

This study utilized multi-source data to analyze the actual conditions of urban green spaces, including built environment data, Points of Interest (POI) data, street view data. Firstly, Python was used to extract built environment data and POI data from Amap (one of the largest map service providers in China). Secondly, fixed-interval sampling points were placed on the roads to capture human-eye perspective images at each sampling point, facilitating the acquisition of street view image data from various streets in Shanghai.

2.4.2. Location

Three evaluation indicators were incorporated into the geographic location dimension: large-scale (commuting) and small-scale (pedestrian walkability) street network accessibility, used to assess the convenience level of reaching park green spaces and the street network accessibility of the two radius was calculated using space syntax (BTA400 and BTA9500). Development intensity were used to assess the construction situation around park green spaces, providing further insight into the population density within the influence area. The calculation method is illustrated in Table 1.

2.4.3. Landscape quality

Existing studies indicate that green cover and street green view index are key features for intuitively assessing the level of greenery in China. The former measures the level of greenery from a macro perspective, while the latter emphasizes the human-scale perception of greenery, effectively quantifying the level of landscape quality. Both are important factors to consider in green city design.

Thus, this study integrated both aspects, jointly serving as evaluation indicators for the landscape quality of urban parks. Green cover was obtained by extracting green elements from satellite images, calculating the proportion of the area after vertical projection, and was used to characterize the two-dimensional greening level of the park, while the street green view index utilized street view images to measure the percentage of green landscape in people's field of vision, serving as an indicator for the three-dimensional level of greening.

2.4.4. Facility levels

To effectively evaluate the facility service level of urban park green spaces, the study selected six categories closely related to people's activities in urban parks from various types of Points of Interest (POI) data. These categories included park landscape features, public facilities, shopping services, educational and cultural services, life services, and sports and leisure facilities. By incorporating two indicators such as POI diversity and service intensity, quantitative assessment of the service level of existing urban park green spaces was conducted with the assistance of ArcGIS.

Table 1. Calculation of dimensional indicators

Dimension	Indicator name	Calculation formula	References
Location	Street network accessibility	$C_b(P_i) = \sum_{j=1}^{n} \sum_{k=1}^{n} \frac{g_{jk}(p_i)}{g_{jk}} (j < k),$ $g_{jk}(p_i)$ is the number of geodesics between node p_j and p_k that contain node p_i, and g_{jk} is the number of all geodesics between p_j and p_k.	Hillier et al., 2005
	Development intensity	$\boldsymbol{Development\ intensity} = \sum_{i=1}^{n} S_i / S_B$ S_i indicates the area of building i within the accessible area and S_B is the area of the buffer.	Zhang et al., 2019
Landscape quality	Green cover	Green cover measured by remote sensing Normalized Difference Vegetation Index (NDVI) from top-down viewpoint.	Ye et al., 2019
	Green view index	Semantic segmentation was utilized to extract different spatial features in street view images. Then, the mean proportion of pixels occupied by vegetation in the four captured images at each sampling point was calculated..	Ye et al., 2019
Facility levels	POI diversity	$\boldsymbol{POI\ diversity} = -\sum_{i=1}^{n} \mathrm{P}i \ln \mathrm{P}i$ P_i indicates the proportion of facility type in building i relative to all facility points within the dail accessible area.	Shannon–Wiener index
	Service intensity	$Service\ intensity = \sum_{i=1}^{n} N_i \Big/ S_A$ N_i indicates the number of facility type in POI categories i relative to all facility points within the accessible area and S_A is the area of the green space.	Zhou et al., 2022

3. Result

3.1. OVERALL EMOTIONAL PERCEPTION

The evaluation volume of the park is highest in March, April, and October, as revealed through an assessment of the entire comment text. The frequent words during these months are illustrated in the following Table.2.

Table 2. High frequency words in each park

Park name	Month with most comments	High frequency content words in this month
Zhongshan Park	April	Peony, Lawns, Cherry blossoms, Tulips
Renmin Park	April	Peony, Blind date, Begonia, Cherry blossoms
Binjiang Park	October	Riverside, Photography, Night scenery, Magnolia, Stroll
Shiji Park	March	Plum blossoms, Cherry blossoms, Weather, Tent

Figure 3 illustrates the evaluation results based on dictionary-based and large language model-based methods. It can be observed that both methods exhibit comparable overall sentiment analysis results for positive, negative, and neutral sentiments. Analyzing sentences with low confidence levels and sentences with dictionary scores between -10 and 10, cross-referenced with star ratings, reveals a higher accuracy in sentiment evaluation by the language model. This approach aligns more closely with actual emotional sentiments. The dictionary-based scoring method encounters challenges when faced with sentences exhibiting significant emotional variations within the same comment, particularly when using irony or employing contrasting expressions. Additionally, confidence values serve as effective indicators for identifying sentences requiring calibration.

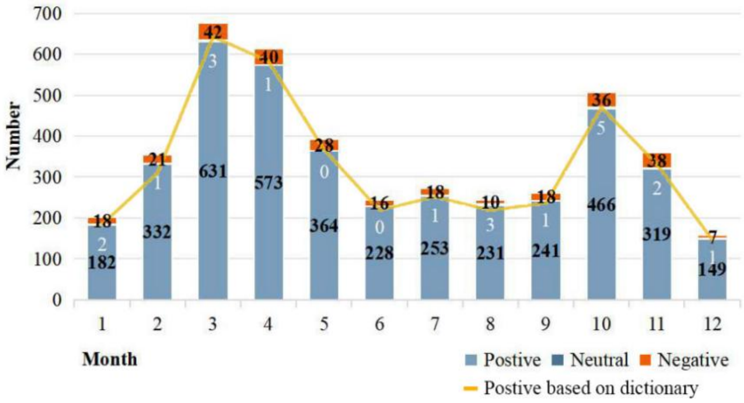

Figure 3. Comparative results of dictionary-based and language model-based methods.

3.2. DIMENSIONAL PERCEPTION AND GREEN SPACE STATUS

3.2.1. Analysis of location

In the location dimension (Figure.4), Renmin Park and Binjiang Park exhibit the highest percentages of positive emotions (95.35% and 94.30%, respectively). The development intensity in Renmin Park and Binjiang Park is 3.03 and 3.44, approximately doubling the construction intensity around the other parks. Additionally, the walkability and commuting accessibility levels of these two parks are significantly higher than the the remaining two parks (Figure.5). The built environment in this dimension has a predominantly positive impact on emotional perception.

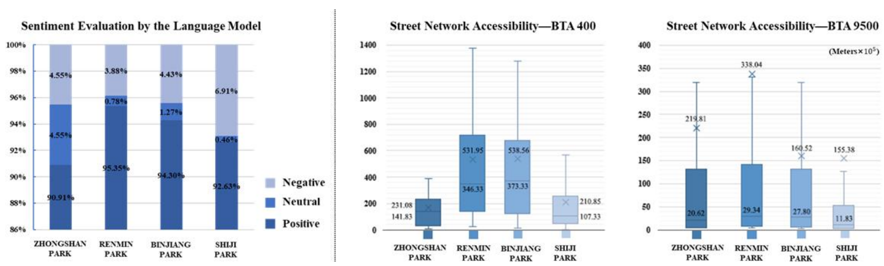

Figure 4. Location comparison across four parks.

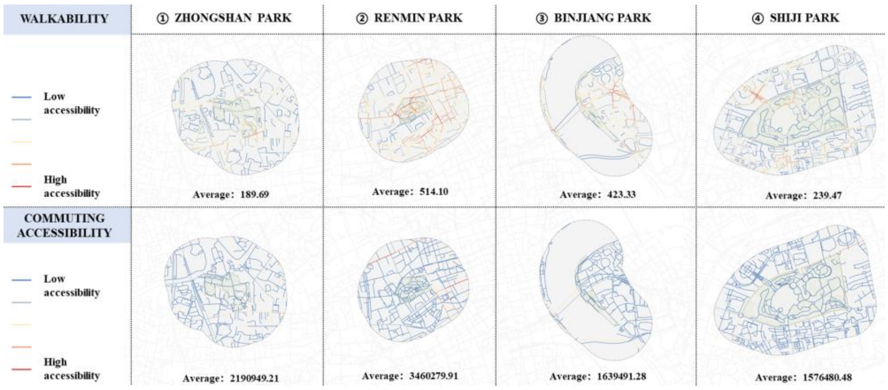

Figure 5. The visualization of street network accessibility.

3.2.2. Analysis of landscape quality

On the landscape quality dimension, the overall proportion of positive emotions was the highest compared to the other three dimensions, around 95%, and the differences in the proportion of positive reviews for each park were not significant (Figure.6). In terms of the overall green view index, Renmin Park ranked the highest. As for the green space cover, Binjiang Park had the lowest coverage, accounting for only 38.36%.

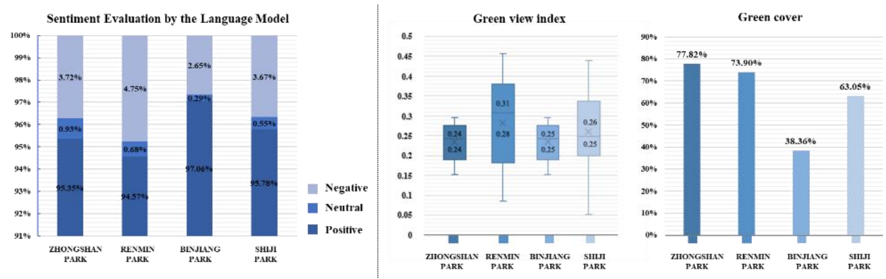

Figure 6. Landscape quality comparison across four parks

3.2.3. Analysis of facility levels

In the facility levels, the positive evaluation proportion and the diversity of facility levels are relatively close among the four parks (Figure.7a). As shown in Figure 8, shopping services dominate in the influence area, and there is a significant disparity in service intensity, with Shiji Park having a much lower service intensity compared to the other parks.

3.2.4. Analysis of management

The overall proportion of negative emotions in the management dimension is the highest among the four dimensions, accounting for 20%-30% of the total (Figure.7b). Even in situations where the actual conditions of the parks are similar, poor park maintenance directly influences visitors' perceptions and emotional experiences.

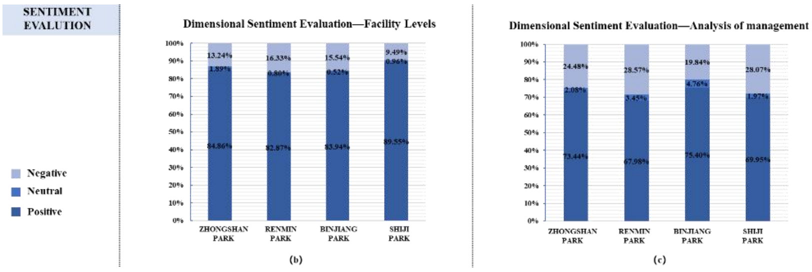

Figure 7. (a) Sentiment evaluation of facility levels. (b) Sentiment evaluation of management.

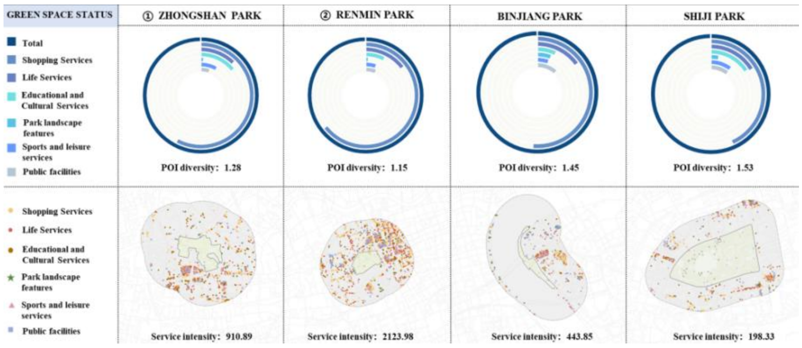

Figure 8. The visualization of POI diversity and service intensity.

4. Conclusion

This study adopted dictionary-based and language model-based methods, offering an analytical framework for reference. In terms of research methodology, text analysis based on language models demonstrates greater flexibility compared to methods relying on dictionaries and machine learning. It allows for personalized downstream tasks by simply adjusting key prompts and exhibits excellent performance in emotion analysis and classification tasks. Furthermore, the research findings reveal a positive relationship between the actual situation and emotional tendencies in the location of park green spaces. Thus, extracting information about the locational dimension from visitor comments can reflect the real situation. As urban green spaces evolve, this study lays the foundation for ongoing investigations into the dynamic interaction between public perception and the actual conditions of parks.

However, certain limitations point to avenues for further exploration. First, expanding the analysis to include additional parks and other relevant information such as park morphology could enrich the study's scope. Second, delving into the actual conditions and evaluation changes around specific events might yield more targeted insights.

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