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**Who Gets Quality Urban Parks? A Socioeconomic Disparity Analysis Using User
Reviews and the Opportunity Algorithm in Los Angeles**

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Who Gets Quality Urban Parks? A Socioeconomic Disparity Analysis Using User Reviews and the Opportunity Algorithm in Los Angeles

Abstract

This study explores urban park equity by leveraging user-generated content from Google Maps and applying the *opportunity algorithm* to assess disparities in park quality. We investigated whether perceived needs and satisfaction levels related to park features vary by neighborhood income level, racial composition, and park size. The opportunity algorithm identifies underserved and overserved features by comparing the relative importance and satisfaction scores. The results revealed that different park groups exhibited distinct underserved and overserved features. Safety concerns are underserved in low-income and minority neighborhoods. Conversely, amenities such as hiking and biking or natural features are often overserved in high-income or high-white areas. Furthermore, dog parks were viewed as overserved in low-white areas but underserved in high-white areas, reflecting a reversed pattern. These findings demonstrate the effectiveness of the opportunity algorithm approach in detecting user perceptions of park quality by identifying mismatches between importance and satisfaction, offering a scalable, data-driven alternative to traditional audits. Based on these insights, we propose policy recommendations to support more inclusive and responsive urban park planning.

Keywords: Urban parks, Inequity, Social media mining, Topic modeling, Sentiment analysis

1. Introduction

Urban parks play a crucial role in providing both ecological and social benefits. As essential components of urban green infrastructure, they offer valuable ecosystem services (Ye et al., 2018; Chiesura, 2004; Rigolon, 2016). Moreover, urban parks create greater opportunities for residents to connect with nature, contributing to the reduction of psychological stress (Fan et al., 2021), fostering social interactions (Hajzeri, 2021), and supporting fitness and recreational activities. These functions collectively enhance the physical and mental well-being of urban communities (Yigitcanlar et al., 2020). However, while parks clearly deliver a bundle of amenities and services, many of these functions, especially those valued subjectively by users, have been underexamined in empirical urban studies.

Recent advances in digital technologies now allow researchers to more comprehensively evaluate how well parks fulfill their various roles. In particular, user-generated content (UGC) from online platforms has emerged as a promising data source for capturing the diverse ways in which urban residents experience and assess public parks (Liu et al., 2024; Chen et al., 2024). Compared to traditional survey-based methods, UGC provides a broader, more dynamic reflection of user perceptions, offering insights into both the presence of amenities and their perceived quality (Martí et al., 2019; Kim & Lee, 2024a). Since visitors are both users and evaluators of parks, analyzing visitor evaluations can provide a more comprehensive understanding of public satisfaction with park recreational quality and inherent differences in park quality (Zou et al., 2024; Zhang et al., 2023). Furthermore, the significance of social media data-driven analysis has grown, particularly following the surge in remote communication through online platforms after the COVID-19 outbreak (Kim, 2023). As a result, UGC from social media and online review platforms is increasingly recognized as a valuable source of information for understanding public perceptions of urban parks (Kim & Lee, 2024a; Song et al., 2020).

Although several recent studies have begun leveraging UGC to evaluate urban environments (Song et al., 2020; Wang et al., 2021), these efforts have often remained exploratory or descriptive. There remains a need for more systematic approaches that can analyze unstructured text data using rigorous quantitative text-mining techniques, especially in ways that account for both user satisfaction and perceived importance. Without such frameworks, the potential of UGC as a tool for evaluating urban park quality remains underutilized.

In response to these gaps, we utilize a methodology from the business field termed the *Opportunity Algorithm* to identify the unmet needs of residents embedded within social media big data (Ulwick, 2002). Originally developed to identify unmet customer needs in product innovation, this approach systematically evaluates features based on their perceived importance and current satisfaction from large-scale UGC. When applied to the urban park context, this method allows researchers to go beyond simply counting numbers of benches or trees and instead, identify park attributes that are most in need of improvement from a user-centered perspective.

As equity concerns surrounding urban parks have grown in scholarly outlets and policy discourse (Boone et al., 2009), understanding whether opportunity patterns differ across income levels, racial composition, and park size can yield important insights. Accordingly, we analyzed how importance-satisfaction patterns vary across different classes of parks and produce findings that reveal specific ways low-income or minority neighborhoods are underserved, demonstrating the advantages of this approach. As a result, this study aims to utilize social media big data to define the built and natural features of urban parks, assess their condition, and identify the aspects most in need of improvement based on park size, racial composition, and income levels. Specifically, this study seeks to address the following research questions.

RQ1. Which park-use topics show a significant mismatch between importance and satisfaction according to the opportunity algorithm?

RQ2. How do the importance–satisfaction gaps differ across parks stratified by income level, racial composition, and park size?

By addressing these questions, this research aims to offer a more systematic and data-driven approach to analyzing unstructured qualitative social media data for urban planning purposes. Through this process, we seek to uncover the latent needs of urban residents embedded in unstructured data, thereby providing more concrete and differentiated policy implications for improving urban park equity.

2. Literature review

2.1. Inequity in urban parks

Urban parks are essential to the lives of city residents, with their physical and mental health benefits well-documented in various studies (Wang et al., 2022; Li et al., 2022). However, it is also evident that urban parks are inherently marked by inequities. Although park-related disparities manifest in multiple ways, many studies addressing park inequity have focused on accessibility in terms of quantity (Rigolon, 2016; Chang et al., 2019; Zhang et al., 2021). On the other hand, some studies have examined urban park quality, often leveraging social media and online review big data to analyze residents' opinions and assess park conditions (Wang et al., 2021; Zhang et al., 2023). Some research has attempted to integrate quantified sentiment analysis into park accessibility calculations to overcome the limitations of unstructured data (Zou et al., 2024). However, there remains a critical gap in systematically analyzing qualitative unstructured data to identify latent needs related to urban park quality using rigorous and quantitative methods. Contemporary inequities are not always overt but rather inherent in the planning, distribution, use, and access of public green and open spaces

(Beck et al., 2024). Therefore, to uncover structural urban inequalities, a more systematic and data-driven approach is necessary.

Increasingly, researchers have studied how access to urban parks differs by socioeconomic and ethnic groups (Wolch et al., 2014). As access to parks is strongly tied to health and social outcomes, recent literature emphasizes the need for equity-driven planning. Globally, disparities in access to urban parks are evident across cities in Europe, Asia, Latin America, and Africa, reflecting broader patterns of environmental and spatial inequality (Kabisch & Haase, 2014). In the U.S., low-income and racially marginalized communities often have fewer parks nearby and significantly less park space per capita than affluent, predominantly white neighborhoods (Rigolon, 2016; Locke et al., 2023). Although some research details mixed results on proximity alone, there is consensus around inequities in park acreage, quality, and amenities, where parks in disadvantaged areas are frequently smaller, less well-maintained, and lack recreational features (Vaughan et al., 2016; Das et al., 2022). These disparities are shaped by historic segregation, unequal public investment, and limited community influence in planning processes (Wen et al., 2013). Additionally, although race and income often overlap, some studies have found that predominantly minority neighborhoods face access gaps even after controlling for income (Locke et al., 2023). Thus, the need to address spatial and qualitative disparities in the aspect of race and income are imperative, while including targeted investment and community engagement (Rigolon, 2016; Das et al., 2022).

2.2. User-generated content

With the growing popularity and scale of social media, millions of daily active users now share images and reviews in real-time on platforms such as Google Maps, Instagram, and Twitter (Song et al., 2020). The vast amounts of data and rich information generated from users' expertise or background are collectively referred to as UGC, characterized by their

public accessibility within these platforms (Gao et al., 2021; Liu et al., 2024). Furthermore, social media data, being directly uploaded by users, functions as a meaningful social listening tool and is actively utilized to understand urban residents' opinions (Park et al., 2021; Chen et al., 2024). Compared to traditional surveys, UGC from social media and online review platforms offers access to large-scale data at a lower cost (Li et al., 2024b; Song et al., 2020). Additionally, because such content is created more spontaneously and unconsciously, it is considered to better reflect users' genuine perspectives (Olteanu, 2019).

In urban research, UGC is widely employed to investigate urban residents' experiences and satisfaction, providing valuable insights into their perspectives and preferences regarding evidence-based park design (Yang & Zhang, 2024; Lee & Kang, 2021). However, many studies evaluating urban parks have tended to focus on physical or spatial accessibility, with limited consideration of how residents actually use and experience these spaces or the variety of ways parks serve community needs. This gap highlights the potential of UGC to complement existing approaches by offering deeper insight into user-centered evaluations of urban parks.

Leveraging the advantages of big data, UGC serves as a powerful tool for analyzing social activities and individual behaviors from a user-centric perspective (Kim & Lee, 2024b). There is some evidence that UGC is a reliable source for examining citizens' perceptions and experiences (Wang et al., 2024; Li et al., 2024a) and their emotional responses (Li et al., 2024b; Zhu et al., 2021). By extracting public perceptions from social media data, researchers can gain insights into user preferences and opinions on urban spaces, contributing to the development of tailored urban planning policies.

2.3. Research gaps

Despite the significant body of research using various methods to assess urban park quality, notable research gaps remain. First, whereas prior research on urban parks has largely focused

on surveys or mobility data, studies utilizing social media data remain scarce. To address this gap, our study leverages Google Maps review data to gain a clearer understanding of public perceptions and take advantage of this particular data source for urban research.

Second, there is a notable lack of studies that employ the opportunity algorithm approach to conduct an in-depth analysis of inequality embedded within urban parks. The opportunity algorithm has been utilized extensively in the business field to analyze customer feedback on products and to identify areas for improvement. Given its applicability in assessing user perceptions and experiences, this approach holds significant potential for urban research, particularly in understanding how residents interact with and utilize urban parks. Nonetheless, few studies have applied this theoretical framework to big data-driven urban analysis.

To fill this gap, our research employs the opportunity algorithm to examine inequalities in urban parks, incorporating socioeconomic and racial factors into the analysis. By doing so, we aim to provide an understanding of disparities within urban parks and identify concrete features for improvement. Furthermore, our findings will offer actionable policy implications for policymakers and urban planners in Los Angeles, contributing to more equitable and inclusive urban park planning.

3. Methodology

This study proposes utilizing Latent Dirichlet Allocation (LDA) topic modeling and the opportunity algorithm from the business field to quantitatively identify areas for improvement in urban parks from a user perspective, based on the following framework to account for demographic characteristics across parks (Figure 1).

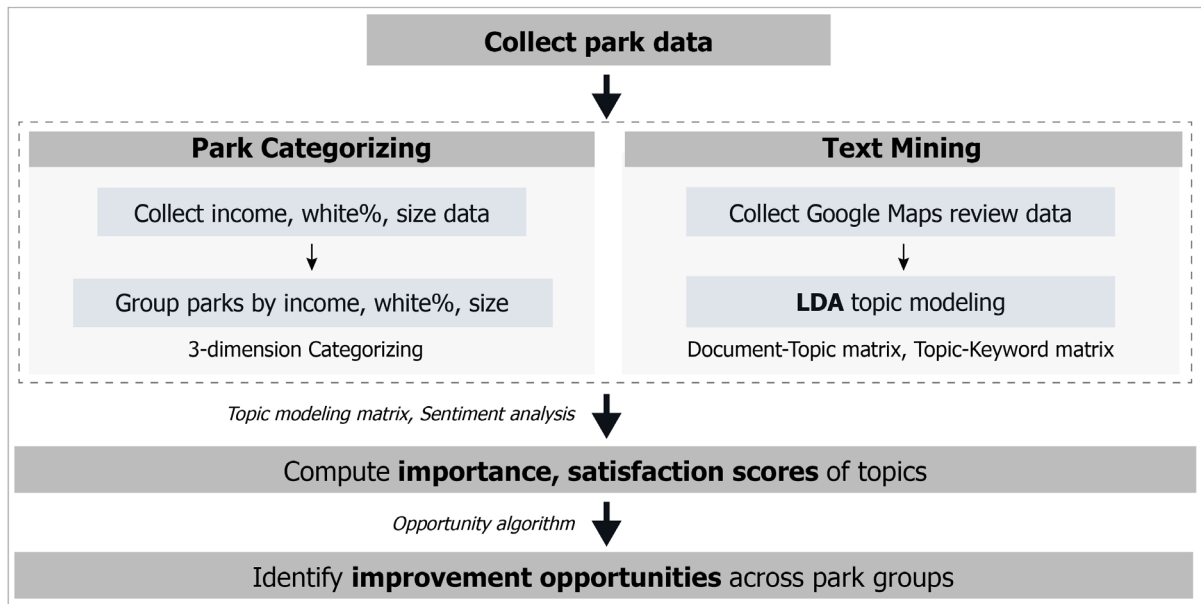


Figure 1. Research framework

3.1. Study area

The spatial scope of this study encompasses parks in the city of Los Angeles (LA), the second largest city in the United States. Specifically, the spatial scope includes all parks provided by the Los Angeles Open Data Portal. LA is known for its distinctive characteristics related to walkability, which are shaped by its diverse built environment, as well as its reputation for high levels of diversity and social segregation. In fact, in 2019, LA was ranked as one of the most racially diverse cities in the United States and placed sixth in terms of social segregation (Gamio, 2019; Menendian et al., 2021). These attributes make LA an ideal setting to achieve the objectives of this study. Although LA serves as the empirical focus due to its demographic diversity and well-documented park inequities, we emphasize the proposed methodological framework is broadly transferable to other cities where user-generated content and socio-demographic data are available.

This study uses individual parks as the unit of analysis. For population and economic data, we chose the block group, a geographic unit employed by the United States Census Bureau to capture neighborhoods. Additionally, block groups are the smallest unit used to access a wide range of socioeconomic variables, including minority variables, provided by the 2017-2021

American Community Survey (ACS) dataset (Ki & Chen, 2023).

Accordingly, the spatial scope of this study comprises a total of 420 parks out of the 564 parks listed in the LA Open Data Portal, excluding those with missing data in Google Maps reviews (Figure 2). For the temporal scope, the study focuses on the period from 2017 to 2021, aligned with the available data.

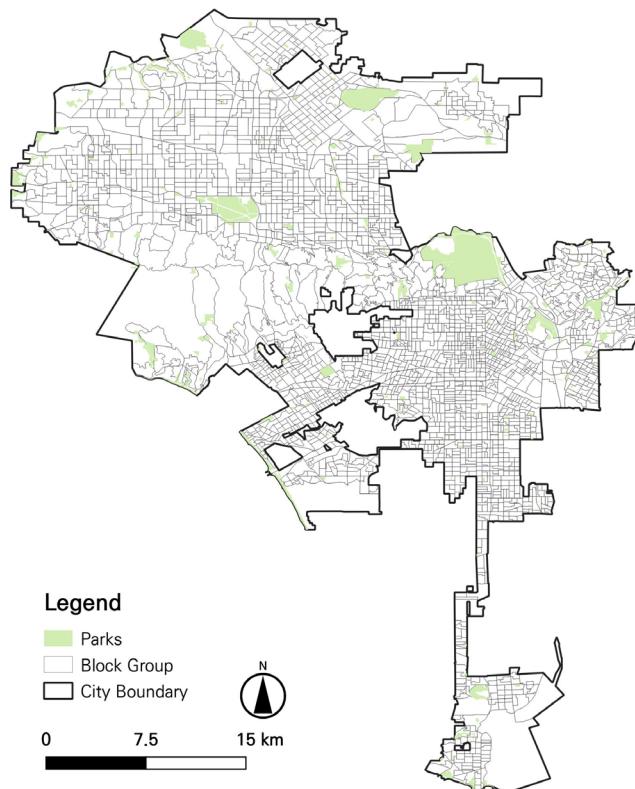


Figure 2. Study area

3.2. Data sources

This study utilized two main categories of data. The first category is socioeconomic and demographic data. We assessed the quality of urban spaces based on three key categories: median income, the percentage of white population, and park size. Income and racial composition are commonly used indicators in studies comparing disparities by race/ethnicity and income, making them relevant for our analysis (Bruton et al., 2014). Additionally, park size serves as a crucial metric for evaluating the quality of urban parks (Rigolon et al., 2018).

We acquired block group-level household income data and race data provided by the census in the 2017–2021 ACS 5-year estimates. For income data, we calculated the average of the median household incomes of the block groups that each park spans. Similarly, for race data, we computed the average percentage of white residents across the block groups intersecting each park. Lastly, we calculated each park’s area using QGIS 3.32.2 to build a dataset for park size. As such, the socioeconomic and demographic data consisted of three variables: income, race, and park size.

The second category is Google Maps review data. This study built a review dataset using the Google Maps API and web scraping. Specifically, we collected reviews by inputting the names of LA parks obtained from the LA Open Data Portal. For web scraping, we used the Selenium and BeautifulSoup packages in Python. We collected reviews only for parks with a minimum of 10 reviews, resulting in data from 420 parks out of 564 listed, with a total of 158,760 reviews. Specifically, we collected information on park names, addresses, review texts, and dates.

3.3. Data preprocessing

First, we removed null and duplicate data. Next, we aligned the data with the study's temporal scope. Finally, we removed non-English reviews using the `'langdetect'` package in Python, resulting in 48,323 reviews from 420 parks, which were used for analysis. Additionally, natural language data acquired from social media typically requires preprocessing steps, including tokenization, stemming, and stop word removal (Vijayarani & Janani, 2016). In this study, we applied stop word removal, text lowercasing, normalization, lemmatization, and tokenization to the review texts.

3.4. Park categorization

This study constructed eight categories of parks based on the three axes of income, percentage of white residents, and park size derived earlier. Specifically, these variables were used to form a three-dimensional space, where parks were divided into eight groups ($2^3 = 8$), depending on whether their values were above or below the median for each axis (Figure 3). Due to the presence of several outliers in the LA region, particularly in terms of park size, we therefore adopted a median-based division approach. The median thresholds were \$79,038.18 for income, 15,929.50m² for area, and 48.59% for racial composition. Based on this classification, Group 1 represents areas with low income, low racial composition, and small parks, all below the median. Group 2 is characterized by high income but low racial composition and small parks. Group 3 includes regions with low income and low racial composition but large parks, while Group 4 combines high income and large parks with low racial composition. Group 5 represents low-income, high-racial-composition, and small-parks clusters, and Group 6 includes high-income, high-racial-composition, and small-parks clusters. Group 7 corresponds to low-income, high-racial-composition, and large-parks regions, whereas Group 8 shows high income, high racial composition, and large parks, indicating that all three variables are above the median.

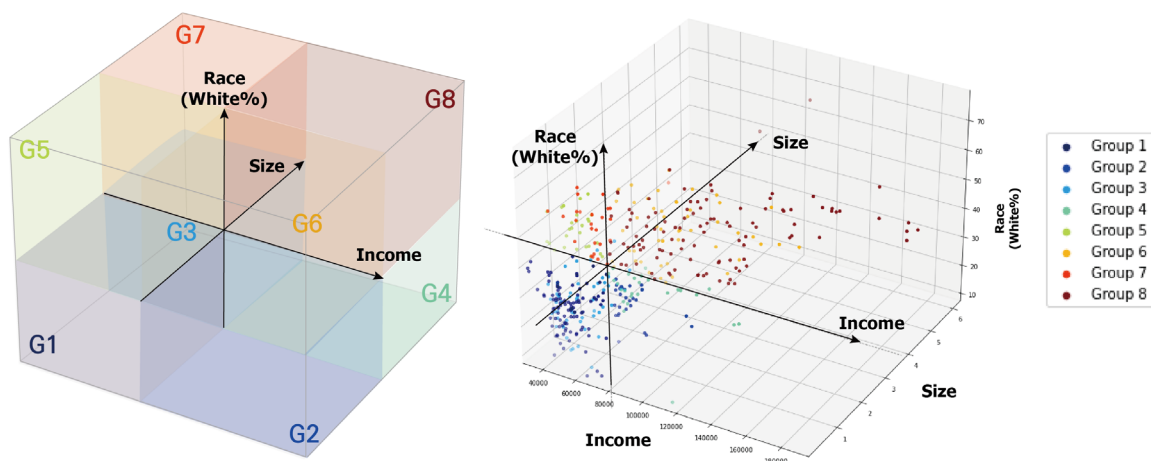


Figure 3. Categorizing process based on three dimensions

3.5. Text mining

3.5.1. LDA Topic modeling

To determine the topics that we will utilize in the opportunity algorithm, we used the popular topic modeling technique, Latent Dirichlet Allocation (LDA). LDA, introduced by Blei et al. (2003), is a probabilistic topic modeling technique based on the Dirichlet distribution. It remains one of the most commonly used topic modeling methods due to its intuitive interpretability (Kim & Lee, 2024a; Egger & Yu, 2022). LDA assumes that a single document can contain multiple topics and is particularly effective for inferring latent topics from text (Jeong et al., 2019). In the context of this study, we derived the underlying topics embedded in LA park reviews using LDA. Additionally, the number of topics is primarily determined based on coherence and perplexity scores.

3.5.2. Sentiment analysis

Sentiment analysis is a field of study that quantitatively measures subjective data such as attitudes and preferences by sorting text into positive and negative categories (Jung et al., 2021). Sentiment analysis is broadly categorized into machine learning-based and dictionary-based. A machine learning-based sentiment analysis judges the sentiment of words in context, considering the weight of sentiment within the context and comprehensively determining the sentiment of the context (Jung et al., 2021). A dictionary-based sentiment analysis judges the polarity of sentiments in sentences based on a predefined sentiment dictionary (Lee et al., 2016). Although a dictionary-based sentiment analysis can be faster and more efficient, it lacks context consideration. Thus, this study conducted machine learning-based sentiment analysis, using RoBERTa, a machine learning-based method, to account for context. Specifically, we employed the RoBERTa-base model, trained on approximately 124 million tweets and fine-tuned for sentiment analysis with the TweetEval benchmark (Barbieri et al., 2020), which has

demonstrated high accuracy across various datasets. Next, we considered negations. Negation words such as "not," "never," "cannot," and "no" were considered. If a negation precedes a token, the sentiment score of the token was flipped. For example, although the phrase "horrible park" assigns a sentiment score of -0.688940 to "horrible," the phrase "not horrible park" assigns a score of +0.688940.

3.6. Opportunity algorithm

The opportunity algorithm was applied to each group of parks based on service quality theory, a framework for evaluating users' perceptions of IT service performance developed by Parasuraman et al. (1988). Grounded in service quality theory within the field of Management Information Systems (MIS), the opportunity algorithm is a method proposed by Ulwick (2005) to prioritize unmet needs. It is used to identify the extent to which each product topic represents a potential opportunity for improvement from a customer-centered perspective (Jeong et al., 2019). Topics identified as underserved or overserved can inform budget allocation, policy design, and urban space enhancement (Choi et al., 2020). This method can help guide decision makers to focus on high-impact opportunities where limited resources can yield the greatest value and help to allocate resources strategically to the most relevant groups (Killen et al., 2005). This approach addresses a key limitation in existing studies, which have rarely attempted to analyze the opportunity level of different citizen demands. Thus, in this study, this method quantifies importance and satisfaction scores for park usage topics and visualizes their positioning using an opportunity landscape map (Jeong et al., 2019).

The opportunity algorithm assumes, in its original product-innovation context, that customers can articulate functional "jobs to be done." Also, it assumes unmet needs arise when the relative importance of a product feature exceeds the satisfaction with its current performance, and market share can grow when resources are directed toward features with the

largest importance–satisfaction gap. When adapting this logic to park service quality, we adopt the same principle of demand–experience discrepancy but acknowledge that park users’ “jobs” are collective and context-dependent rather than tied to discrete product attributes. Accordingly, we applied some modifications. We conducted the analysis on each of the eight groups sequentially to capture local variability in park supply and user expectations. This adjustment clarifies the algorithm’s boundaries, while highlighting relative priorities within the observed parks. The process is divided into four main steps.

Step 1: Identifying park usage topics using LDA topic modeling

In this step, park usage topics are identified from the review data constructed earlier through LDA topic modeling. LDA requires three inputs: a corpus, a word dictionary, and the number of topics (Jeong et al., 2019). The corpus and word dictionary in this context refer to the total reviews and the tokens extracted from the structured review text, respectively. The number of topics is generally determined based on perplexity and coherence scores. Perplexity scores evaluate how well an LDA predicts unseen data and coherence scores measure the semantic similarity of top words in topics (Hasan et al., 2021). Lower perplexity and higher coherence scores indicate an appropriate number of topics, and sharp changes in these metrics are typically chosen.

Step 2: Quantifying importance scores of park usage topics

The usage topics generated by LDA topic modeling represent the major subjects people discuss in relation to parks, derived from user-generated online review data. Additionally, the importance of each usage topic is measured by the degree to which it is mentioned. Specifically, the sum of the contribution probabilities of each topic across reviews in a group represents the topic's importance within the collected corpus (Figure 4a). This importance score is normalized

on a scale of 0 to 10 using min-max scaling (Equation 1),

$$\overline{I_{n,i}} = 10 \times \frac{I_{n,i} - I_{Min,i}}{I_{Max,i} - I_{Min,i}} \quad \text{Equation (1)}$$

where $I_{n,i}$ denotes the original importance score of topic n for group i , $\overline{I_{n,i}}$ represents the normalized importance score of topic n for group i , $I_{Min,i}$ and $I_{Max,i}$ indicate the minimum and maximum importance scores within group i . Since higher topic contribution probability indicates a stronger presence of that topic in public discourse, this normalized score serves as a valid proxy for latent public “demand” for each topic. This process is repeated for each group, yielding importance scores for each topic within each of the eight groups.

Step 3: Quantifying satisfaction scores of park usage topics

In the third step, satisfaction levels are quantified. To achieve this, sentiment analysis is first performed on all keywords in the previously constructed word dictionary to calculate sentiment weights. Next, each element of this matrix was multiplied by the same element in the topic-keyword matrix generated in the previous step to construct a sentiment-weighted topic stock. Thus, satisfaction is calculated by multiplying each element of the sentiment-weighted keyword matrix by the corresponding element in the topic-keyword matrix and summing the results. This satisfaction score was normalized on a scale of 0 to 10 using min-max scaling for comparability across topics and groups (Equation 2)

$$\overline{S_{n,i}} = 10 \times \frac{S_{n,i} - S_{Min,i}}{S_{Max,i} - S_{Min,i}} \quad \text{Equation (2)}$$

where $S_{n,i}$ denotes the original satisfaction score of topic n for group i , $\overline{S_{n,i}}$ represents the normalized satisfaction score of topic n for group i , $S_{Min,i}$ and $S_{Max,i}$ indicate the minimum and maximum satisfaction scores within group i . This process was repeated for each group, yielding satisfaction scores for each topic across the eight groups (Figure 4b). Since positive sentiment represents favorable user experiences, this normalized score is treated as a valid

proxy for “experience satisfaction.”

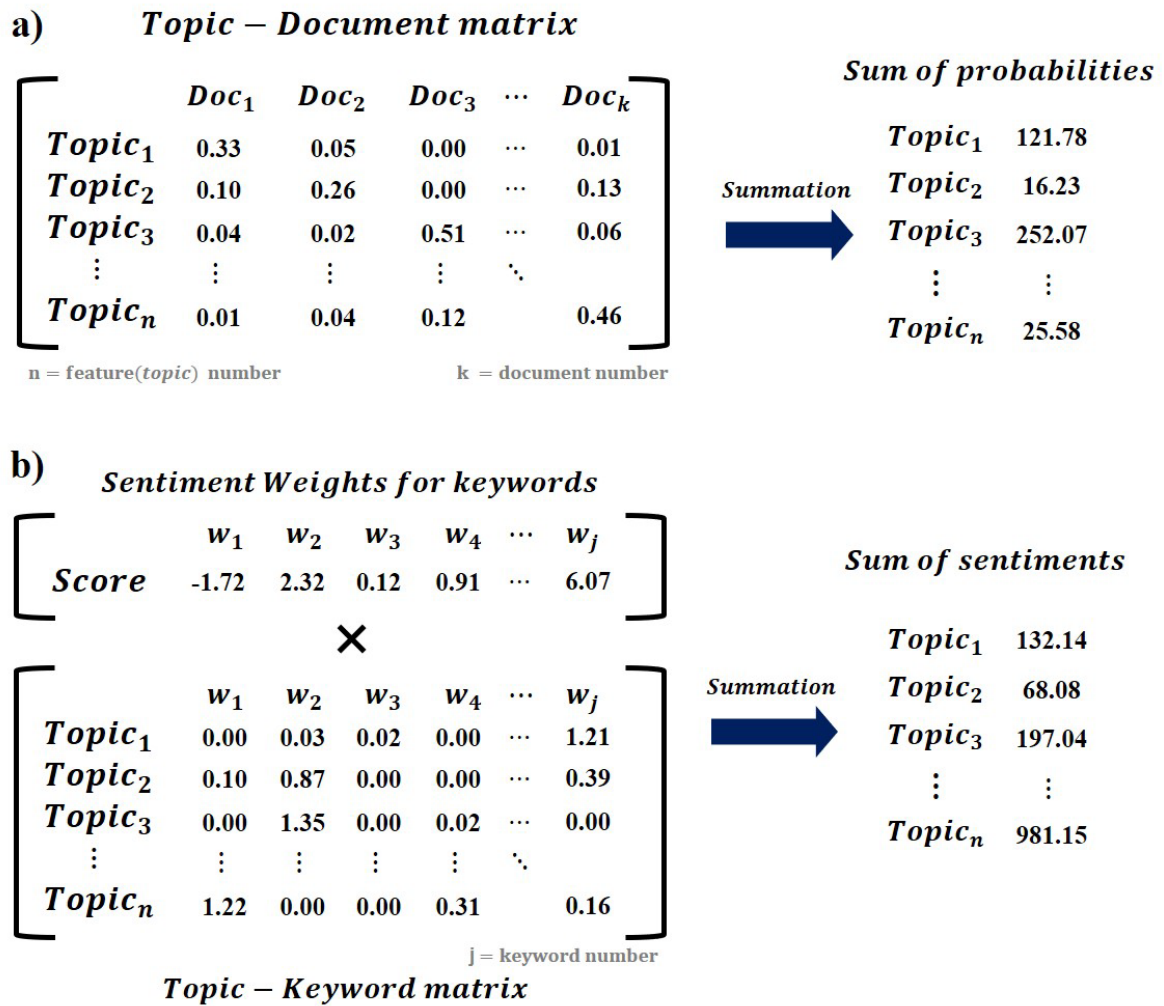


Figure 4. Computing the importance(a), satisfaction(b) score of park usage topics

Step 4: Identifying improvement opportunities (topics)

In the final step, importance scores and satisfaction scores obtained in the previous steps are set as axes to identify opportunity topics for each group. To create baselines on the map, we calculated the mean importance and satisfaction scores for each group (Equations 3, 4).

$$\bar{I}_l = \frac{1}{N} \sum_{n=1}^N \bar{I}_{n,l} \quad \text{Equation (3)}$$

$$\bar{S}_l = \frac{1}{N} \sum_{n=1}^N \bar{S}_{n,l} \quad \text{Equation (4)}$$

where *N* is total number of the topic (*N* = 50 in this study). Then we drew an importance baseline from the average importance score to the point (10,10) and a satisfaction baseline

from the average satisfaction score to the same point. Additionally, we applied a 1,000-iteration bootstrap at the topic level to estimate interval ranges for importance and satisfaction and mentioned in each figure's caption. This process creates a map divided into three regions: the "Served-Right" region, where both importance and satisfaction scores are adequately met, the "Overserved" region, where satisfaction is high relative to low importance, and the "Underserved" region, where satisfaction is low relative to high importance (Figure 5). According to the opportunity algorithm, unmet needs in the "Underserved" region represent opportunities for improvement. This method was applied to each group, ultimately producing eight opportunity maps. By comparing the topics across groups, this study examines the inequalities embedded in LA's urban parks from a socioeconomic perspective. The algorithmic structure and groupwise mapping logic are adaptable to other urban contexts, enabling comparative assessments of perceived service quality across cities.

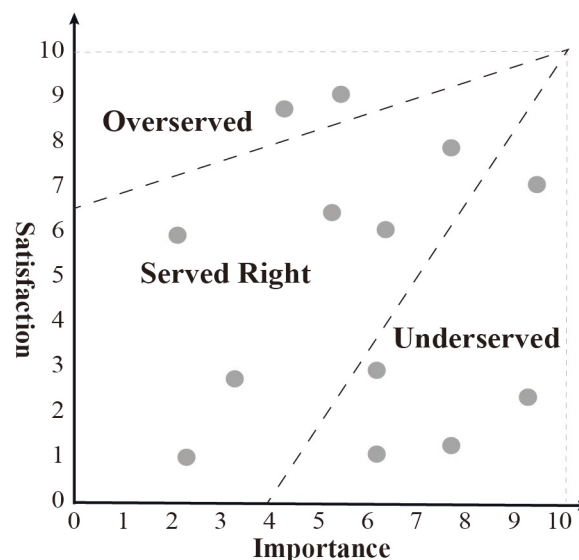


Figure 5. Conceptual diagram of the opportunity map

Source: Adapted from Jeong et al. (2019)

4. Results

4.1. Descriptive analysis of categorizing

The eight distinct groups of parks are summarized in Table 1. Groups 8 and 1 emerged as the most populated, comprising 106 and 104 parks, respectively. Group 8 represents parks that score above the average across all three key features (income, race, and park size), whereas Group 1 consists of parks that fall below average on all three metrics. In terms of review volume, Group 8 and 3 exhibit significantly higher engagement, with 18,683 and 10,630 reviews, respectively. Interestingly, despite Group 1 containing twice as many parks as Group 3, it recorded substantially fewer reviews. Although Groups 1 and 3 share similarities in income levels and proportion of white residents, both being below the average, they diverge in terms of park size. When analyzing the average number of reviews per park, Groups 3, 4, 8, and 7 lead in engagement metrics. Notably, it appears that larger parks tend to receive the most reviews per park.

Table 1. Features and counts of each group

Group	Mean			Park Counts	Review Counts	Average review counts per park
	Income (\$)	Race (% of white)	Size (m ²)			
1	Low 55,049.67	Low 30.27	Low 5,660.11	104	6,906	66
2	High 92,394.83	Low 38.80	Low 6,140.78	28	1,386	50
3	Low 59,707.81	Low 32.00	High 112,509.38	52	10,630	204
4	High 101,072.09	Low 42.01	High 141,631.96	26	4,812	185
5	Low 61,109.63	High 57.71	Low 6,077.79	28	1,526	55
6	High 119,472.12	High 66.86	Low 5,620.98	50	3,844	77
7	Low 68,095.40	High 58.84	High 219,282.77	26	3,614	139
8	High 135,458.98	High 67.50	High 281,393.46	106	18,683	176

*Income median: \$79,038.18, Race median: 48.59%, Size median: 15,929.50m²

*High: value $\geq$ median, Low: value $<$ median

*Average review counts per park = $\frac{\text{Review Counts}}{\text{Park Counts}}$

4.2. LDA topic modeling

The results of topic modeling using the LDA are briefly presented in Table 2. A

comprehensive summary of all 50 topics, including top keywords and representative sentences, is provided in Table S1 of the Supplementary Material. The number of topics was determined to be 50, based on perplexity and coherence scores (Figures S1-S2, Supplementary material). Using the top keywords for each topic (Table S2, Supplementary material), topic labels were assigned with the assistance of ChatGPT-4o in order to objectively identify the central themes of the extracted topics (Kim & Lee, 2024a). We used the prompt “Based on the top words, interpret them, understand the meaning of the topic, and create a representative topic name.” Additionally, we manually reviewed the results and ensured that the topic names were not misleading. For example, Topic 1 included keywords ‘dog’, ‘awesome’, ‘park’, ‘leash’, and ‘run’, resulting in the topic name ‘Dog Parks and Leash Policies’.

Table 2. LDA topic modeling results

Num.	Topic Name	Count	Num.	Topic Name	Count
0	Local Community and Public Spaces	961	25	Security Issues	473
1	Dog Parks and Leash Policies	1,826	26	Walking Trails and Road Conditions	2,527
2	Cleanliness and Safety of Public Spaces	815	27	Sports Fields and Peaceful Recreation	1,133
3	Neighborhood and City Parks	906	28	Peaceful Morning Parks	734
4	Family-Friendly Fun Areas	775	29	Dog Walking Parks	1,043
5	Night Light and Accessibility	738	30	Wildlife-Friendly Parks	822
6	Homeless People	671	31	Dangerous and Homeless People	634
7	Natural and Historical Places	479	32	Multi-Sport Parks and Playgrounds	1,891
8	Weekend Outdoor Places	708	33	Quiet and Cleanliness	745
9	Climbing and Adventures	590	34	Beautiful Green Spaces	1,747
10	Golf and Nature Observation	709	35	New Serene Parks	294
11	Architectural Spaces	699	36	Smoke, Drugs and Trash	445
12	Hidden Gem and Renewal	457	37	Family-Friendly Park for Kids and Pets	1,391
13	Exercise and Clean Air	896	38	Safety Concerns and Homeless	1,061
14	Historical Tour and Pokemon Spaces	424	39	Family and Friends	1,243
15	Hiking and Biking	1,429	40	Public Art and Monuments	714
16	Sports Atmosphere	624	41	Well-Maintained Facilities	957

17	Beautiful and Peaceful	594	42	Kid-Friendly Parks for Walk	2,421
18	Scenery and Calmness	630	43	Lighting and Night Safety	1,426
19	Waterfront Scenery	645	44	Dog-Friendly Park	599
20	Scenic Outdoor Parks and Gatherings	612	45	Recreation and Rest Areas	2,154
21	Walking Trails and Paths	1,215	46	Spacious Shaded Areas	553
22	Relaxation and Meditation	2,336	47	Highly Recommend Amenities	702
23	Clean Parks with Limited Facilities	1,004	48	Cleanliness Issues	558
24	Cultural Parks and Local Events	488	49	School Programs and Gatherings	825

The identified topics generally encompass perceptions, activities, and issues related to parks. Topics related to perceptions, such as Topics 17, 18, and 33, are characterized by an emphasis on adjectives, which reflects how users describe their sensory experiences that can also be understood as integral components of park services. Topics related to activities, including Topics 9, 24, and 29, cover various aspects such as exercise, local events, and dog walking, reflecting common and engaging park activities. Issues-related topics, such as Topics 6, 36, and 48, highlight concerns related to homelessness, indiscriminate smoking, and cleanliness, capturing distinct challenges faced by parks. Overall, the extracted topics effectively reflect the characteristics of parks across LA.

4.3. Opportunity algorithm

4.3.1. Opportunity mapping

This study calculated the importance and satisfaction scores for each group (Table S3) and conducted opportunity mapping to identify the distribution of each topic. By applying an opportunity algorithm to analyze topic-level improvement factors based on individual reviews, this facilitates the identification of potential enhancements for parks.

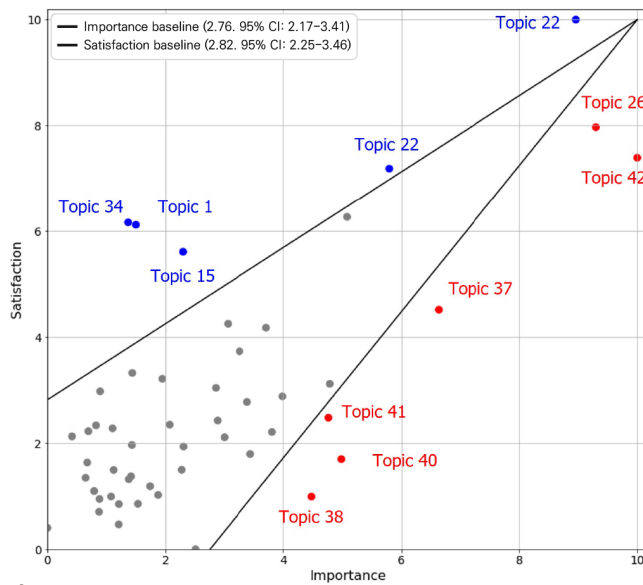
The opportunity map clearly visualizes differing perceptions of topics across groups. In the opportunity map, the red points represent underserved topics, which are characterized by high importance but low satisfaction. The blue points indicate overserved topics, which have

low importance but high satisfaction. The gray points denote served-right topics, where both importance and satisfaction are balanced. For space reasons, we present results for four major groups to illustrate disparities in urban park experiences. The results of mapping topics across these four groups are presented in Figures 6 and 7. The remaining groups' figures are included in the Supplementary material (Figures S3–S6).

Group 1 is characterized by features including low income, a low percentage of white residents, and small park size. As shown in Figure 6a, in this group, topics related to family activities, such as Topics 37 and 42, were identified as underserved. Additionally, safety concerns related to homelessness (Topic 38) and issues regarding trails and facilities (Topics 26, 41) also exhibited low satisfaction relative to their importance. Conversely, topics related to exercising (Topics 15, 32) and relaxation (Topics 22, 34) were classified as overserved.

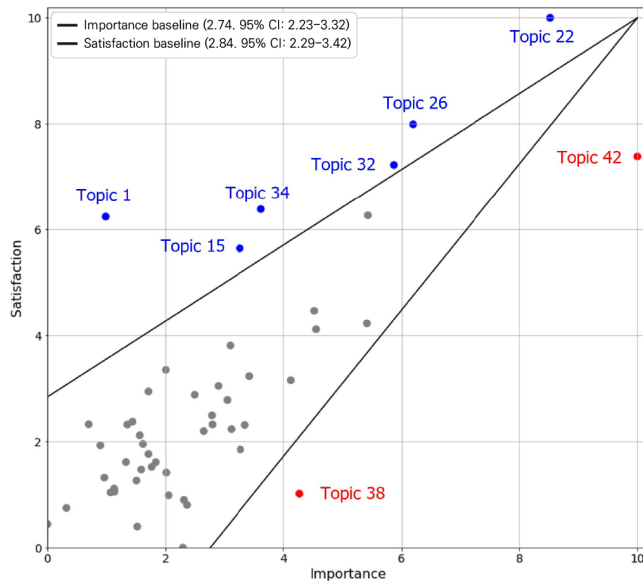
Group 3 is similar to Group 1 in that it is characterized by low income and a low percentage of white residents, but differs in that it has large park sizes. For this group in Figure 6b, safety concerns related to homelessness (Topic 38) were identified as a critical issue, with high importance but low satisfaction, indicating a need for improvement. Similarly, kid-friendly amenities (Topic 42) were also found to require enhancement. Conversely, topics related to exercising (Topics 15, 32), relaxation (Topics 22, 34), and activities involving dogs and walking (Topics 1, 26) were classified as overserved. The distribution of overserved topics in this group closely resembles that of Group 1.

a) Group 1



Underserved	
Topic 26	Walking Trails and Road Conditions
Topic 37	Family-Friendly Park for Kids and Pets
Topic 38	Safety Concerns and Homeless
Topic 40	Public Art and Monuments
Topic 41	Well-Maintained Facilities
Topic 42	Kid-Friendly Parks for Walk
Overserved	
Topic 1	Dog Parks and Leash Policies
Topic 15	Hiking and Biking
Topic 22	Relaxation and Meditation
Topic 32	Multi-Sport Parks and Playgrounds
Topic 34	Beautiful Green Spaces

b) Group 3



Underserved	
Topic 38	Safety Concerns and Homeless
Topic 42	Kid-Friendly Parks for Walk
Overserved	
Topic 1	Dog Parks and Leash Policies
Topic 15	Hiking and Biking
Topic 22	Relaxation and Meditation
Topic 26	Walking Trails and Road Conditions
Topic 32	Multi-Sport Parks and Playgrounds
Topic 34	Beautiful Green Spaces

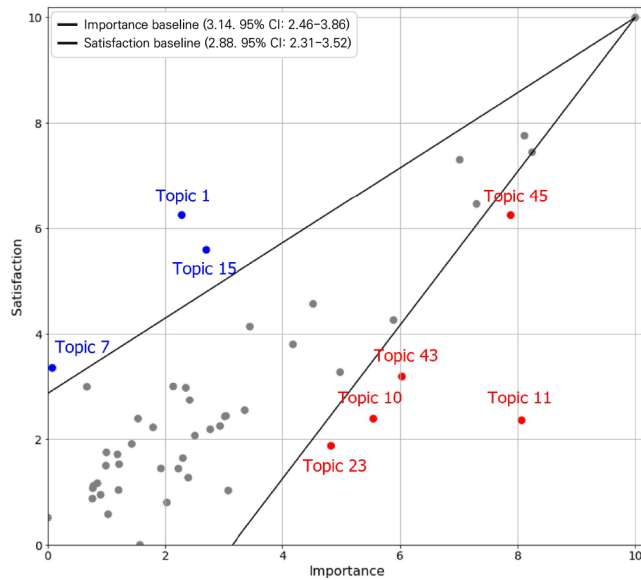
Figure 6. Opportunity mapping results of Group 1 (a), Group 3 (b)

Group 7 is characterized by low income, a high percentage of white residents, and large park sizes. As shown in Figure 7a, several aspects were identified as requiring improvement. Specifically, nature-related aspects (Topic 10), architectural features (Topic 11), cleanliness (Topic 23), night safety (Topic 43), and recreation and rest (Topic 45) were all classified as underserved, indicating a need for targeted interventions. Conversely, several topics were found to be overserved, with satisfaction exceeding perceived importance. These included dogs and walking (Topic 1), natural spaces (Topic 7), and hiking (Topic 15), suggesting that these

aspects are rated with relatively high satisfaction despite their lower importance ratings.

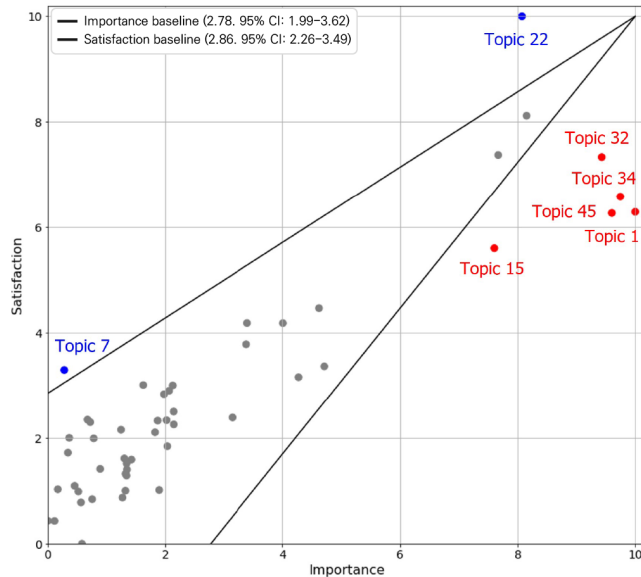
Group 8 is characterized by high income, a high percentage of white residents, and large park sizes. We can see in Figure 7b that several aspects were identified as requiring improvement. Specifically, dogs and walking (Topic 1), hiking (Topic 15), sports facilities (Topic 32), green spaces (Topic 34), and recreation and rest (Topic 45) were classified as underserved, indicating the need for enhancements in these areas. Interestingly, although these all received above average satisfaction scores, they also all have *very* high importance to these residents and therefore, are classified as underserved. Conversely, topics related to natural spaces (Topic 7) and relaxation (Topic 22) were found to be overserved, with satisfaction levels exceeding their perceived importance.

a) Group 7



Underserved	
Topic 10	Golf and Nature Observation
Topic 11	Architectural Spaces
Topic 23	Clean Parks with Limited Facilities
Topic 43	Lighting and Night Safety
Topic 45	Recreation and Rest Areas
Overserved	
Topic 1	Dog Parks and Leash Policies
Topic 7	Natural and Historical Places
Topic 15	Hiking and Biking

b) Group 8



Underserved	
Topic 1	Dog Parks and Leash Policies
Topic 15	Hiking and Biking
Topic 32	Multi-Sport Parks and Playgrounds
Topic 34	Beautiful Green Spaces
Topic 45	Recreation and Rest Areas
Overserved	
Topic 7	Natural and Historical Places
Topic 22	Relaxation and Meditation

Figure 7. Opportunity mapping results of Group 7(a), Group 8(b)

4.3.2. Opportunity by dimensions

Table 3, along with Tables S4 and S5 in the Supplementary material, provide the same information, but each is ordered differently to emphasize one of the dimensions. For example, Table 3 is broadly sorted by parks in low and high income neighborhoods, and we see that topic 15 “Hiking and Biking”, was consistently classified as ‘Overserved’ in low-income areas. This suggests that in these neighborhoods, the perceived satisfaction with this topic exceeds its importance, indicating an oversupply. Likewise, multi-sport parks (Topic 32), dog parks

(Topic 1), relaxation and meditation (Topic 22), and beautiful green spaces (Topic 34) were all generally overserved in low-income areas. In contrast, Topic 38, “Safety Concerns and Homeless”, was classified as ‘Underserved’ exclusively in parks in low-income areas, whereas it was categorized as ‘Served-Right’ in other park groups. This finding suggests that in low-income neighborhoods, particularly those with lower proportions of white residents, concerns about homelessness and safety are more pronounced, with satisfaction levels falling below the perceived importance.

Table 3. Topics in groups by income

Num.	Topic Name	Low income				High income			
		1 ↓↓↓	3 ↓↓↑	5 ↓↑↓	7 ↓↑↑	2 ↑↓↑	4 ↑↓↑	6 ↑↑↓	8 ↑↑↑
1	Dog Parks and Leash Policies	Over	Over	Under	Over		Over	Under	Under
4	Family-Friendly Fun Areas							Over	
7	Natural and Historical Places			Over	Over	Over		Over	Over
8	Weekend Outdoor Places			Under					
9	Climbing and Adventures						Under		
10	Golf and Nature Observation				Under				
11	Architectural Spaces				Under	Under			
15	Hiking and Biking	Over	Over	Over	Over			Over	Under
21	Walking Trails and Paths					Under			
22	Relaxation and Meditation	Over	Over	Over			Under	Over	Over
23	Clean Parks with Limited Facilities					Under			
26	Walking Trails and Road Conditions	Under	Over	Under	Under		Over	Under	
27	Sports Fields and Peaceful Recreation			Over				Over	
30	Wildlife-Friendly Parks			Under					
32	Multi-Sport Parks and Playgrounds	Over	Over	Over		Over	Under	Over	Under
33	Quiet and Cleanliness					Under			
34	Beautiful Green Spaces	Over	Over	Over		Over		Over	Under
37	Family-Friendly Park for Kids and Pets	Under						Over	
38	Safety Concerns and Homeless	Under	Under						
39	Family and Friends							Over	

40	Public Art and Monuments	Under		Under		Under			
41	Well-Maintained Facilities	Under							
42	Kid-Friendly Parks for Walking	Under	Under			Under	Under	Over	
43	Lighting and Night Safety				Under				
45	Recreation and Rest Areas			Over	Under	Under	Under	Over	Under

Note: The arrows below the group number respectively indicate income, proportion of whites, and park size

Next, we examined the results based on the proportion of white residents (Table S4, Supplementary material). Notably, the most significant patterns emerged in Topic 38, Safety Concerns and Homeless, and Topic 42, Kid-Friendly Parks for Walk, both of which were predominantly classified as underserved. This indicates that parks in areas with lower white population proportions tend to have greater safety concerns and a lack of pedestrian and child-friendly amenities. This trend aligns with the findings from Table 2, where parks in lower-income neighborhoods also exhibited safety-related concerns. Conversely, Topic 7, Natural and Historical Places, was consistently classified as overserved in parks in areas with a higher white population proportion. This suggests lower perceived importance despite high satisfaction. The most striking contrast was observed in Topic 1, Dog Parks and Leash Policies. In areas with a lower white population proportion, dog parks were classified as overserved, whereas in areas with a higher proportion of white residents, they were mostly categorized as underserved. This indicates that in neighborhoods with a lower white population proportion, the perceived importance of dog parks is relatively low, leading to an overserved classification even with moderate satisfaction. In contrast, in areas with a higher white population proportion, the importance of dog parks is significantly higher, resulting in an underserved classification despite moderate satisfaction levels. These findings highlight a critical insight derived from our opportunity mapping: communities with a higher proportion of white residents place greater emphasis on pet-friendly park amenities, reflecting both a higher demand and concerns for improvement. Several underlying factors may contribute to this pattern. Differences in pet

ownership rates across demographic groups could play a role, as previous studies have shown higher dog ownership among whites (Mueller et al., 2021). In addition, higher land values in white-majority neighborhoods may limit the feasibility of allocating large dedicated spaces for off-leash areas. Community norms and local governance priorities regarding animal control, shared space etiquette, or enforcement of leash policies may also vary, influencing how residents perceive adequacy.

Lastly, we examined the results based on the size of the park (Table S5, Supplementary material). The analysis revealed that Topic 26, Walking Trails and Road Conditions, was consistently classified as underserved in smaller parks. Whereas larger parks exhibited a mix of overserved and underserved classifications, smaller parks showed a clear trend of dissatisfaction with trails. Similarly, Topic 40, Public Art and Monuments, was predominantly categorized as underserved in smaller parks, indicating that aesthetic elements in these parks did not meet users' expectations. In contrast, Topic 32, Multi-Sport Parks and Playgrounds, and Topic 34, Beautiful Green Spaces, were consistently classified as overserved in smaller parks. This suggests that in these parks, the perceived satisfaction with these amenities exceeds their importance, indicating a potential oversupply. Finally, dog parks (Topic 1) were generally overserved in large parks, but often underserved in small parks, whereas the pattern was reversed for recreation and rest areas (Topic 45).

5. Discussion

Our analysis of park usage experiences across eight groups stratified by income, racial composition, and park size reveals some notable disparities. In lower income, majority minority neighborhoods, users frequently cited safety, maintenance, and limited amenities, with concerns about illicit activity common. For example, Topic 38 (“Safety Concerns and Homeless”) consistently emerged as underserved in parks in low-income and low-white

neighborhoods, underscoring the urgency of addressing public safety and related conditions. In contrast, parks in higher income, majority white neighborhoods, especially larger parks, received more favorable reviews emphasizing cleanliness, aesthetics, and recreational amenities. Consistent with prior research, parks in low-income neighborhoods tend to be underutilized not solely due to a lack of facilities, but also because perceived threats such as crime, poor maintenance, and social disorder function as significant barriers to use, shaping dissatisfaction around safety and upkeep (Cohen et al., 2012; Weiss et al., 2011). These perceptions are not isolated to park design alone but are deeply embedded in broader neighborhood conditions. Given that studies have shown that the higher crime in more disadvantage neighborhoods can bleed into the parks of those neighborhoods (Boessen & Hipp, 2018), our results show that this is a challenge for creating parks that are satisfactory to residents. The evidence from other research on the type of park features associated with more crime will also be helpful in guiding policy decisions (Groff & McCord, 2011).

Notably, disparities persisted even among parks of similar size, highlighting the role of socioeconomic and racial contexts. A particularly notable finding is Topic 1 (“Dog Parks and Leash Policies”), which showed a reversed pattern: overserved in low-white areas but underserved in white-majority areas. This likely reflects differences in expectations where dog-friendly amenities are seen as more important in white-majority neighborhoods, leading to lower perceived satisfaction despite moderate provision. Such findings illustrate that equity challenges are not solely about the absence of amenities, but about mismatches between what communities value and what is delivered, revealing an imbalance that traditional access-based studies or metrics may fail to capture. This contrast highlights how our opportunity mapping captures mismatches between need and experience, not just service levels. Importantly, our results move beyond conventional equity analyses focused solely on access or quantity by foregrounding mismatches between perceived importance and satisfaction, offering a more

nuanced understanding of service quality. This shift reframes park equity as not only a matter of physical provision but also of experiential, recognition, and procedural justice, highlighting whose needs are prioritized and how user voices are represented in park governance.

Our findings align with longstanding patterns of park inequity in Los Angeles. Prior research has consistently shown that low-income communities of color experience significantly reduced park access (Wolch et al., 2005; Minaravesh, 2025). This study builds upon this foundation by emphasizing differences in user-perceived quality. For instance, a community led audit in south LA, a predominantly low-income, minority area, assigned local parks a grade of “F”, while parks in the more affluent Santa Monica area received a grade of “C” (National Health Foundation, 2019), illustrating systemic underinvestment. This study highlights how structural disparities are reflected in park quality perceptions, reinforcing the critical link between environmental justice and urban planning.

Methodologically, it is important to note that this study introduces an innovative approach to evaluating park equity through large-scale use of UGC. Unlike traditional audits, UGC captures real-time, organically produced, user-centered insights into public experiences that are difficult to document through surveys. Also, by applying the opportunity algorithm to online park reviews, we were able to systematically quantify public perceptions across a wide range of parks. This approach offers a scalable and dynamic alternative to traditional audit-based assessments, allowing for more continuous monitoring of park conditions (Walter et al., 2023). Although the study was retrospective in nature, the underlying methodology presents potential for near-real-time monitoring and operational integration, especially when compared to the limitations of manual audits, which are often labor-intensive, costly, and conducted infrequently. This approach can help governments monitor emerging issues, inform responsive maintenance strategies, and enhance transparency in park management practices. Furthermore, it has strong potential for serving as a dashboard to help governments prioritize inspections

and investments.

The findings point toward several policy directions. First, equity-oriented funding should guide the allocation of park resources, with explicit prioritization of investments in low-income, high-need communities (Rigolon et al, 2024). Second, inclusive design standards must ensure that all parks, regardless of location or size, provide clean, safe, and functional amenities based on community needs (National Health Foundation, 2019). Third, expanding programming and staffing, particularly in underserved areas, can improve park safety, foster social cohesion, and increase usage (Cohen et al., 2016). Fourth, the mismatches identified through our approach suggest that planners should move beyond uniform standards and instead consider adopting targeted, topic-specific interventions. For example, prioritizing safety-oriented design and maintenance in parks where safety is highly valued but poorly rated is essential, while reallocating resources away from overserved amenities. Finally, integrating data-driven tools into planning processes would enable ongoing evaluation of park performance and help translate user feedback into concrete improvements. Such participatory mechanisms can strengthen procedural justice by ensuring that user-generated feedback meaningfully informs planning and investment decisions. Addressing park inequities requires not only physical expansion of green space but also sustained commitment to equitable maintenance, design, and engagement strategies that center the lived experiences of marginalized communities.

6. Conclusion

This study offers a novel, data-driven approach to evaluating park equity by leveraging large-scale UGC and applying the opportunity algorithm. By analyzing perceived importance versus satisfaction across thematic topics, we identified disparities in park experiences based on income, racial composition, and park size. The opportunity mapping framework revealed mismatches between community needs and experiences, providing actionable insights for more

equitable park planning.

Our findings contribute to both urban planning and environmental justice literatures by highlighting not only disparities in park access, but also in perceived quality and user experience. Methodologically, our approach demonstrates the potential of integrating natural language processing into equity analysis, offering a scalable tool for real-time monitoring and community-responsive planning. This study also highlights the methodological novelty of combining topic modeling, context-sensitive sentiment analysis, and the opportunity algorithm to evaluate perceived park quality at scale. By enabling dynamic, user-centered evaluations, this approach can serve as an operational tool for monitoring urban park equity in near-real time. Furthermore, while the analysis focuses on Los Angeles, the underlying framework is generalizable and can be applied to other cities seeking to evaluate and improve equity in public space experiences using user-generated data.

Although this study offers a novel quantitative framework for evaluating park equity and provides policy insights, it is important to acknowledge several limitations. First, although we employed RoBERTa-based sentiment analysis to capture contextual meaning as possible, some contextual nuances may be underrepresented. Future work will incorporate user ratings alongside sentiment scores to enhance accuracy. Second, this study lacks ground-truth validation. As we did not conduct systematic comparisons with field audits or third-party environmental quality assessments, but rely primarily on online reviews, sample bias may exist. In particular, online reviews often reflect the voices of more digitally active users, potentially excluding perspectives from elderly or digitally marginalized groups. While this study relied exclusively on Google Maps reviews for consistency and coverage, future research could incorporate complementary data sources or distinguish between visitor and resident perspectives to provide a more comprehensive understanding of park experiences. To address this, we propose incorporating additional qualitative methods such as interviews or

community-based surveys to better capture underrepresented experiences. Finally, our study period spans both the pre- and post-COVID-19 era, raising the possibility that behavioral shifts induced by the pandemic may be embedded in the results. Prior studies have reported that residents have increasingly used parks perceiving as lower-risk environments, or shifted more toward online services to avoid infection risks (Kim & Lee, 2024a; Ugolini, 2020), potentially influencing patterns of spatial and service usage. However, we did not incorporate the temporal dimension into our analysis, as multiple analytical dimensions were already considered. Nonetheless, our supplementary validation showed no notable differences between pre- and post-COVID-19 periods, indicating that both time spans provided stable and comparable review samples. As online park reviews often capture episodic rather than longitudinal experiences, future research could extend our framework by explicitly examining temporal dynamics to uncover how public perceptions and usage behaviors evolve over time.

Despite these limitations, our approach offers a promising pathway for data-informed park equity assessments and underscores the importance of centering lived experiences in public space management and policy making.

References

1. Barbieri, F., Camacho-Collados, J., Neves, L., & Espinosa-Anke, L. (2020). TweetEval: Unified benchmark and comparative evaluation for tweet classification. arXiv preprint arXiv:2010.12421.
2. Beck, H., Berney, R., Kirk, B., & Yocom, K. P. (2024). Building equity into public park and recreation service investment: A review of public agency approaches. *Landscape and Urban Planning*, 247, 105069.
3. Blei, D. M., Ng, A. Y., & Jordan, M. I. (2003). Latent dirichlet allocation. *Journal of Machine Learning Research*, 3(Jan), 993-1022.
4. Boone, C. G., Buckley, G. L., Grove, J. M., & Sister, C. (2009). Parks and people: An environmental justice inquiry in Baltimore, Maryland. *Annals of the Association of American Geographers*, 99(4), 767-787.
5. Boessen, A., & Hipp, J. R. (2018). Parks as crime inhibitors or generators: Examining parks

and the role of their nearby context. *Social Science Research*, 76, 186-201.

6. Bruton, C. M., & Floyd, M. F. (2014). Disparities in built and natural features of urban parks: comparisons by neighborhood level race/ethnicity and income. *Journal of Urban Health*, 91, 894-907.
7. Chang, Z., Chen, J., Li, W., & Li, X. (2019). Public transportation and the spatial inequality of urban park accessibility: New evidence from Hong Kong. *Transportation Research Part D: Transport and Environment*, 76, 111-122.
8. Chen, M., Cai, Y., Guo, S., Sun, R., Song, Y., & Shen, X. (2024). Evaluating implied urban nature vitality in San Francisco: An interdisciplinary approach combining census data, street view images, and social media analysis. *Urban Forestry & Urban Greening*, 95, 128289.
9. Chiesura, A. (2004). The role of urban parks for the sustainable city. *Landscape and Urban Planning*, 68(1), 129-138.
10. Cohen, D. A., Han, B., Derose, K. P., Williamson, S., Marsh, T., Raaen, L., & McKenzie, T. L. (2016). The paradox of parks in low-income areas: Park use and perceived threats. *Environment and Behavior*, 48(1), 230-245.
11. Cohen, D. A., Han, B., Derose, K. P., Williamson, S., Marsh, T., Rudick, J., & McKenzie, T. L. (2012). Neighborhood poverty, park use, and park-based physical activity in a Southern California city. *Social Science & Medicine*, 75(12), 2317-2325.
12. Das, K. V., Xu, Y., & Bowman, C. (2022). Unearthing inequities in park access and quality: A block-group analysis in a Southern U.S. city. *International Journal of Environmental Research and Public Health*, 19(5), 2871
13. Egger, R., & Yu, J. (2022). A topic modeling comparison between lda, nmf, top2vec, and bertopic to demystify twitter posts. *Frontiers in Sociology*, 7, 886498.
14. Fan, Z., Duan, J., Lu, Y., Zou, W., & Lan, W. (2021). A geographical detector study on factors influencing urban park use in Nanjing, China. *Urban Forestry & Urban Greening*, 59, 126996.
15. Ghahramani, M., Galle, N. J., Ratti, C., & Pilla, F. (2021). Tales of a city: Sentiment analysis of urban green space in Dublin. *Cities*, 119, 103395.
16. Groff, E., & McCord, E. S. (2012). The role of neighborhood parks as crime generators. *Security Journal*, 25(1), 1-24.
17. Hajzeri, A. (2021). The management of urban parks and its contribution to social interactions. *Arboricultural Journal*, 43(3), 187-195.
18. Jeong, B., Yoon, J., & Lee, J. M. (2019). Social media mining for product planning: A product opportunity mining approach based on topic modeling and sentiment analysis. *International Journal of Information Management*, 48, 280-290.
19. Jung, J., Chung, H., & Lee, Z., (2021). An analysis of mobile food delivery app 'Baemin' by using text mining and ARIMA model. *Journal of Digital Contents Society*, 22(2), 291-299.

20. Kabisch, N., & Haase, D. (2014). Green justice or just green? Provision of urban green spaces in Berlin, Germany. *Landscape and Urban Planning*, 122, 129–139.
21. Killen, C. P., Walker, M., & Hunt, R. A. (2005). Strategic planning using QFD. *International Journal of Quality & Reliability Management*, 22(1), 17-29.
22. Ki, D., & Chen, Z. (2023). Walkability inequity in Los Angeles: Uncovering the overlooked role of micro-level features. *Transportation Research Part D: Transport and Environment*, 122, 103888.
23. Kim, Y. (2023). A Study on Corona Depression Using Big Data. *Health and Social Welfare Review*, 43(2), 29-47.
24. Kim, H., & Lee, S. (2024a). Analysis of Changes in Urban Space Usage for Alleviating Depression Before and After COVID-19 - Application of KoBERTopic Model with Social Media Bigdata. *Journal of the Urban Design Institute of Korea Urban Design*, 25(2), 109-125.
25. Kim, H., & Lee, S. (2024b). POI GPT: Extracting POI Information from Social Media Text Data. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, 48, 113-118.
26. Lee, S., Cui, J., & Kim, J., (2016). Sentiment analysis on movie review through building modified sentiment dictionary by movie genre. *Journal of Intelligence and Information Systems*, 22(2), 97-113.
27. Li, J., Gao, J., Zhang, Z., Fu, J., Shao, G., Zhao, Z., & Yang, P. (2024a). Insights into citizens' experiences of cultural ecosystem services in urban green spaces based on social media analytics. *Landscape and Urban Planning*, 244, 104999.
28. Li, L., Hu, S., Shaw, A., & Hemphill, L. (2024b). Crowdsourcing public attitudes toward local services through the lens of Google Maps reviews: An urban density-based perspective. *arXiv preprint arXiv:2404.13156*.
29. Li, Z., Liang, Z., Feng, L., & Fan, Z. (2022). Beyond accessibility: a multidimensional evaluation of urban park equity in yangzhou, China. *ISPRS International Journal of Geo-Information*, 11(8), 429.
30. Liu, S., Tan, C., Deng, F., Zhang, W., & Wu, X. (2024). A new framework for assessment of park management in smart cities: a study based on social media data and deep learning. *Scientific Reports*, 14(1), 3630.
31. Locke, D. H., et al. (2023). Racial, ethnic, and socioeconomic disparities in multiple measures of blue and green spaces in the United States. *Environmental Health Perspectives*, 131(1), 17001.
32. Martí, P., Serrano-Estrada, L., & Nolasco-Cirugeda, A. (2019). Social media data: Challenges, opportunities and limitations in urban studies. *Computers, Environment and Urban Systems*, 74, 161-174.
33. Minaravesh, B. (2025). Identifying concentrations of overlapping environmental & economic insecurity in Los Angeles County. *Applied Geography*, 178, 103575.
34. National Health Foundation. (2019). *Unveiling the Root Causes of Park Inequity in South*

Los Angeles. Retrieved from <https://nationalhealthfoundation.org/unveiling-the-root-causes-of-park-inequity-in-south-los-angeles/#:~:text=Historic%20South%20Central%20averaged%20an,138%2C000%20to%20Santa%20Monica%E2%80%99s%2093%2C000>

35. Parasuraman, A., Zeithaml, V. A., & Berry, L. L. (1988). Servqual: A multiple-item scale for measuring consumer perc. *Journal of Retailing*, 64(1), 12.
36. Plunz, R. A., Zhou, Y., Vintimilla, M. I. C., Mckeown, K., Yu, T., Uguccione, L., & Sutto, M. P. (2019). Twitter sentiment in New York City parks as measure of well-being. *Landscape and Urban Planning*, 189, 235-246.
37. Rigolon, A. (2016). A complex landscape of inequity in access to urban parks: A literature review. *Landscape and Urban Planning*, 153, 160-169.
38. Rigolon, A., Browning, M., & Jennings, V. (2018). Inequities in the quality of urban park systems: An environmental justice investigation of cities in the United States. *Landscape and Urban Planning*, 178, 156-169.
39. Rigolon, A., Giamarino, C., & Christensen, J. (2024). Development fees and park equity in Los Angeles. *Journal of the American Planning Association*, 90(2), 230-246.
40. Song, Y., Fernandez, J., & Wang, T. (2020). Understanding perceived site qualities and experiences of urban public spaces: A case study of social media reviews in Bryant Park, New York City. *Sustainability*, 12(19), 8036.
41. Ugolini, F., Massetti, L., Calaza-Martínez, P., Cariñanos, P., Dobbs, C., Ostoić, S. K., ... & Sanesi, G. (2020). Effects of the COVID-19 pandemic on the use and perceptions of urban green space: An international exploratory study. *Urban Forestry & Urban Greening*, 56, 126888.
42. Ulwick, A.W. (2002). Turn customer input into innovation. *Harvard Business Review*, 80(1), 91-97.
43. Ulwick, A. (2005). *What customers want* (Vol. 8). New York, NY: McGraw-Hill Professional Publishing.
44. Vaughan, K. B., et al. (2016). Socioeconomic and race/ethnic disparities in observed park quality. *BMC Public Health*, 16(1), 395.
45. Walter, M., Bagozzi, B. E., Ajibade, I., & Mondal, P. (2023). Social media analysis reveals environmental injustices in Philadelphia urban parks. *Scientific Reports*, 13(1), 12571.
46. Wang, X., Meng, Q., Liu, X., Allam, M., Zhang, L., Hu, X., ... & Jancsó, T. (2022). Evaluation of fairness of urban park green space based on an improved supply model of green space: A case study of Beijing central city. *Remote Sensing*, 15(1), 244.
47. Wang, Z., Miao, Y., Xu, M., Zhu, Z., Qureshi, S., & Chang, Q. (2021). Revealing the differences of urban parks' services to human wellbeing based upon social media data. *Urban Forestry & Urban Greening*, 63, 127233.
48. Wang, Y. (2024). Fusing multi-source social media data and street view imagery to inform urban space quality: a study of user perceptions at Kampong Glam and Haji Lane. *Urban*

Informatics, 3(1), 21.

49. Weiss, C. C., Purciel, M., Bader, M., Quinn, J. W., Lovasi, G., Neckerman, K. M., & Rundle, A. G. (2011). Reconsidering access: park facilities and neighborhood disamenities in New York City. *Journal of Urban Health*, 88(2), 297-310.
50. Wen, M., Zhang, X., Harris, C., & Holt, J. (2013). Spatial disparities in the distribution of parks and green spaces in the USA. *Annals of Behavioral Medicine*, 45(S1), 18–27.
51. Wolch, J., Wilson, J. P., & Fehrenbach, J. (2005). Parks and park funding in Los Angeles: An equity-mapping analysis. *Urban Geography*, 26(1), 4-35.
52. Wolch, J. R., Byrne, J., & Newell, J. P. (2014). Urban green space, public health, and environmental justice: The challenge of making cities ‘just green enough’. *Landscape and Urban Planning*, 125, 234-244.
53. Yang, C., & Zhang, Y. (2024). Public emotions and visual perception of the East Coast Park in Singapore: A deep learning method using social media data. *Urban Forestry & Urban Greening*, 94, 128285.
54. Ye, C., Hu, L., & Li, M. (2018). Urban green space accessibility changes in a high-density city: A case study of Macau from 2010 to 2015. *Journal of Transport Geography*, 66, 106-115.
55. Yigitcanlar, T., Kamruzzaman, M., Teimouri, R., Degirmenci, K., & Alanjagh, F. A. (2020). Association between park visits and mental health in a developing country context: The case of Tabriz, Iran. *Landscape and Urban Planning*, 199, 103805.
56. Zhang, R., Sun, F., Shen, Y., Peng, S., & Che, Y. (2021). Accessibility of urban park benefits with different spatial coverage: Spatial and social inequity. *Applied Geography*, 135, 102555.
57. Zhang, Y., Yan, S., Liu, J., & Xu, P. (2023). Popularity influence mechanism of creative industry parks: A semantic analysis based on social media data. *Sustainable Cities and Society*, 90, 104384.
58. Zhu, X., Gao, M., Zhang, R., & Zhang, B. (2021). Quantifying emotional differences in urban green spaces extracted from photos on social networking sites: A study of 34 parks in three cities in northern China. *Urban Forestry & Urban Greening*, 62, 127133.
59. Zou, N., Mi, X., Xiao, Y., Li, Y., & Hu, N. (2024). Assessing urban park equity in Chaoyang District, Beijing using online review data. *Scientific Reports*, 14(1), 1160.