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User Perception of Public Parks: A Pilot Study Integrating Spatial Social Media Data with Park Management in the City of Chicago

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Abstract: User-generated content (UGC) is a relatively young field of research; however, it has been proven useful in disciplines such as hospitality and tourism, to elicit public opinions of place usage. In landscape architecture and urban planning, UGC has been used to understand people's emotions and movement in a space, while other areas and additional functions are yet to be discovered. This paper explores the capability of UGC in revealing city-scale park management problems and the applicability of social media as a future tool in bridging visitor feedback to city parks and recreation department staff. This research analyzed the spatial characteristics and patterns of Google Maps review quantity, rating score, and review comments. The results of this pilot study indicate the spatial and structural features of the Chicago parks and demonstrate distribution problems, financial investment priority concerns, park usage characteristics, and user preferences of the park attributes. Findings affirm that user-generated online reviews can be used as an alternative and self-reporting data source to effectively assess the natural performance and users' experience of city parks and can potentially serve as an evaluative tool for public park management.

Keywords: user-generated content (UGC); park and recreation; Google Maps; online views; park experience

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1. Introduction

1.1. Urban Parks and Parks-and-Recreation in Cities

Urban parks are defined as delineated open space areas, which are mostly dominated by vegetation and water, and generally reserved for public use [1]. Parks vary in size; while most urban parks are large, some can be small and are called "pocket parks". Parks are usually defined by authorities, are typically owned and managed by their local municipality and/or government agencies, and aim to provide sports, physical activities, cultural and environmental programs to local residents and visitors [2]. Urban parks and public open spaces are crucial to livable and sustainable cities and towns. The experience of nature in urban environments can elicit positive feelings and beneficial services that satisfy the social functions and psychological needs of its users [3]. They are important assets to cities and have been shown to provide tremendous benefits to urban dwellers' wellbeing. For example, the presence of natural assets and components in an urban context can reduce stress [4] and provide a sense of peacefulness [5]. Live plantings, such as trees and grass in outdoor spaces, may promote social connectedness [6]. Trees, water, and open spaces, especially attractive ones, are also associated with higher house prices and have the potential to bring economic benefits to the surrounding neighborhood [7].

Urban parks should be inclusive for urban dwellers and visitors as the accessibility, quality, and availability of urban parks impact life in cities [8]. In the United States, the municipality's parks' management agency, typically its parks and recreation department, plays an important role in monitoring an accessible and equitable distribution of urban parks to visitors. According to the Park and Recreation Professional's Handbook, with the current challenges the world faces, including inequity, obesity, polities, and technology development among others, park and recreation professionals have many opportunities to engage with people's leisure time, understand people's needs, and continue to play a stronger role in improving lives [2]. As public amenities and a form of public investment, urban parks should serve communities fairly, especially for those with inadequate access to private recreational activities, such as low-income populations, older adults, youth, and ethnic minorities [9].

1.2. Current Park Management Strategy Challenges

A city's parks and recreation department is responsible to provide places and programming that help residents and visitors of all ages, backgrounds, and economic and social status stay healthy and learn new skills. With large quantities of facilities and huge areas to manage, doing this job likely faces many challenges. Some frequently mentioned challenges include:

(a) New methods are required to keep information up to date.

Traditionally, and even today, the standard practices to monitor park usage and performance are surveys, questionnaires, and observations. For example, Cohen et al.'s two-year study looked at the relationship between park usage, park characteristics and demographic factors. They surveyed 51 park directors and more than 4000 park users and residents, and conducted observations on 30 parks in a Southern California metropolitan area [10]. Chiesura distributed 750 questionnaires to understand the significance of nature in citizens' well-being and the contribution to the sustainability of the city [1]. In a case of neighborhood parks performance assessment in New Orleans, the researchers conducted observations on a total of 39 neighborhood parks with more than 170 activity areas. To maintain research rigidity, the observations were conducted six times per day, with a half-hour interval over a three-hour period [11]. Those methods provide a sufficient dataset if conducted right. However, they are typically limited by staff capacity in terms of time and number of employees, can be potentially costly to conduct, especially regularly, and are not always spatially explicit [12].

Many internal and external factors and changes may impact park visitation and usage, and it may be difficult to maintain up-to-date information under current monitoring methods. For example, Zhang and Zhou found that transportation accessibility is a significant factor in park usage [13]; however, city administrators normally do not conduct a survey of park usage before and after the construction of every new bus stop. The same story applies to the COVID-19 pandemic, that typical information generating methods, such as questionnaires and surveys, are not sufficient to draw any meaningful conclusions on how the usage pattern or visiting groups change over time, or under particular circumstances. Adopting and implementing new methods to generate data about gathering patterns, popular programs, and immediate concerns is an urgent task for parks and recreation departments to undertake.

(b) Data collection and park performance measurements require improvement.

As the recreational division owns or maintains a large and complicated array of programs located in different places that are aligned with different operating models, and target various customer groups, maintaining a simple and consistent way of data collection and performance measurement is challenging. Previously and currently, as aforementioned, data is often collected via surveys and questionnaires to solicit community feedback. However, those methods are often lacking in fidelity due to the lack of participation of certain populations, especially those who are marginalized. For instance, Scott and Munson's study revealed that low-income family members' park usage were limited by many reasons, including fear of crime, health conditions, transportation, and costs. Moreover, members of low-income groups have always been under-sampled, due to reasons such as busy work schedule or family duties [14]. The city of Seattle's Recreational Evaluation Plan pointed out that to prioritize recreational services for underserved communities, additional data collection and reporting is needed [15].

All data collection, analysis, and performance measurement require a certain level of educational background, professional accountability, continued training and professional development [16]. Who has the skillsets to do these analyses? How many times and how often do park and recreational staff members normally conduct a survey? How are data interpreted and how are those interpretations used for future park development and planning? How can community members be involved in data contribution and monitoring performance evaluation processes? All these questions are important but remain unanswered and ripe for novel solutions.

(c) Environmental justice problems and efforts from planning.

Research has found that green spaces are inequitably distributed within cities. Cities in UK, Australia, Turkey, and the US, have reported that the so-called minority groups are often disproportionally displaced to areas with less access to urban open spaces, and may consequentially be exposed to greater health-related issues [17]. Byrne, Wolch, and Zhang argue in their systematic review that although many recent park usage articles attempt to explain differences in park visits based on factors such as race, gender, and age, they ignore important social-spatial factors that may support park use. Geographical variables such as residential location, park distribution, and facility supply must also be considered as potentially relevant factors for park use and as such, require more in-depth investigation [17].

To battle with existing environmental justice problems, an equity-oriented approach to landscape planning that better articulates park needs, recreational and health disparities, and park resources distribution is required [18]. Some previous research, most of which utilized ArcGIS and open city data, has begun to shed light on future planning efforts. Previous discussed topics mostly include park proximity, acreage, and park qualities [19]. These quantitative analyses show multifaceted patterns of environmental injustice. However, to retrieve feedback and perceptions from residents and affected groups, additional qualitative data needs to be acquired for further analysis.

(d) Insufficient budget and financial investment.

Another factor is sometimes drawn from insufficient funding from public entities. Takyi and Seidel showcased a case study of parks in the city of Vancouver to illustrate the fact that the indirect economic values of urban parks make it difficult to represent their financial benefits. This affects the ability to assess the true costs and benefits for decision makers. This adversely impacts the level of investment in the ongoing development of the park, thereby limiting sustainable management of the entire park system [20]. To become more effective in dealing with rising costs associated with providing basic services, park and recreation agencies have had to become more business-like [21], which may lead to uneven attention to all the parks in city.

1.3. User-Generated Content and Its Potential to Contribute to Landscape Governance

With the development of science and technology, as well as the proliferation of electronic device usages in daily life, the forms of information we can gather have also changed. There has been a shift in mindset about how to collect and analyze data in public re-digital formats to obtain better and more innovative results. User-generated content, or UGC, is one form of data that has effects on society, economy, and individuals [22]. According to Wyrwoll, UGC is content that is published on online platforms by users, through a process that does not require users to be equipped with programming skills. Social media then comprises platforms that contain user-generated content [22].

The innovation of UGC is that it consists of different forms of data, which enlarges the scope and aspects of the data characteristics. It may help researchers further examine the correlations of data content with other information, for example, demographic records. A traditional UGC unit consists of core data, or the content, and metadata, or the information about the given piece of information, such as the date and time of publication, the associated author information, and the number of views [22]. Moreover, one of the benefits of UGC is that almost all the content is voluntarily uploaded by users, so the content itself is unobtrusive, and reduces the researchers' need to be directly involved in data collection.

In terms of disciplines, journalism, computer science, media and culture, marketing, hospitality, and tourism are employing UGC research. The most researched social media platforms are Twitter, Flickr, YouTube, Facebook, and Instagram, to name a few. User-generated content is being used to understand customer needs [23], such as how it may change users' behavior and travel habits [24], and how it provides first-time users the opportunity to understand a place by exploring the descriptions and opinions from others [25].

The authors believe UGC has potential to contribute to a better understanding of environmental experiences and landscape governance, and in turn with the generated information, to help parks and recreation staff more efficiently manage entities within their city scale. In the field of landscape architecture, several social media platforms have been studied and have contributed to the understanding of user movements, perceptions, and feature popularities within or outside parks. Examples include Flickr and Twitter data which can showcase human visitation dynamics and indicate the equitability of park access [26]. Flickr images can be analyzed to explore people's perception and attitudes towards a phenomenon in city parks [27]. Instagram posts can be collected and coded to understand users' emotions and activities associated with specific park features [28].

There is currently limited research utilizing Google Maps user reviews to understand park management deficiencies or visitor feedback on park conditions. However, Google reviews have been utilized in other fields, to examine airport service quality [29], restaurant service and customer's eating experience [30], students' educational experience and their attitudes towards quality of teaching, course design, learning environment and support received [31], and so on. Google Maps user reviews have also been used for branding tourist destinations and to predict public perceptions of visiting places [32]. However, as reported, few of these studies have focused on using the core data, the content metadata, spatially explicit information, or the other values associated with the core data.

This project is a pilot study intending to make breakthroughs in this area, through further use of metadata, especially the spatial attributes of core data, and to analyze the relationship between core data, metadata, and other data that exists within the city boundary on websites. This analysis may help to support the use of UCG as a relevant assessment tool for future park management of any city. The objective of this paper is to use Google Map reviews of Chicago public parks as an example of UCG to determine a relationship between popularities of reviews together with their spatial pattern, most-discussed topics, and the corresponding relationship with household incomes, population distribution, and the equality of regional development.

2. Data and Methods

2.1. Study Area

The authors chose the city of Chicago to conduct a pilot study for several reasons. Chicago has long been an experimental mecca for urban design, planning, and landscape architecture. In Dreaming the Metropolis [33], Cronon described the importance of land geography in Chicago, and how the location of resources, transportation routes, and culture shaped the city to what we know today. Chicago also has geographically related inequities including health disparities [34], healthy food access [35], and transportation and mobility issues [36]. Chicago also has one of the largest urban public park districts in the world staffed by 3000 full-time and 3000 seasonal employees in the 2000s [16]. The Chicago Park District now has the stewardship of more than 8000 acres of open spaces, more than 570 parks, 30 plus beaches, and 50 nature areas [37]. Moreover, the city of Chicago has public demographic data that are accessible to researchers, and Chicago's parks also have received large quantities of reviews on Google Maps which made the quantitative analysis abundant in samples.

As aforementioned, the social media platform for this research is Google Maps. All the parks analyzed in this research were registered as parks under the official Chicago Park District website [38]. The core data reviewed in this paper are the review content, including the comments and review scores, which range from 1 to 5, with 1 being the lowest and 5 being the highest for their satisfaction with the Chicago urban parks. The boundary of this project follows the city boundary set by the planning and development department, as shown by Figure 1. The reviews of the parks that were studied are drawn from the amenity lists from the Chicago Park District. Pertinent to this paper, the Google review average score, numbers of ratings, as well as the first five reviews are public data that can be collected by anyone (see Figure 2).

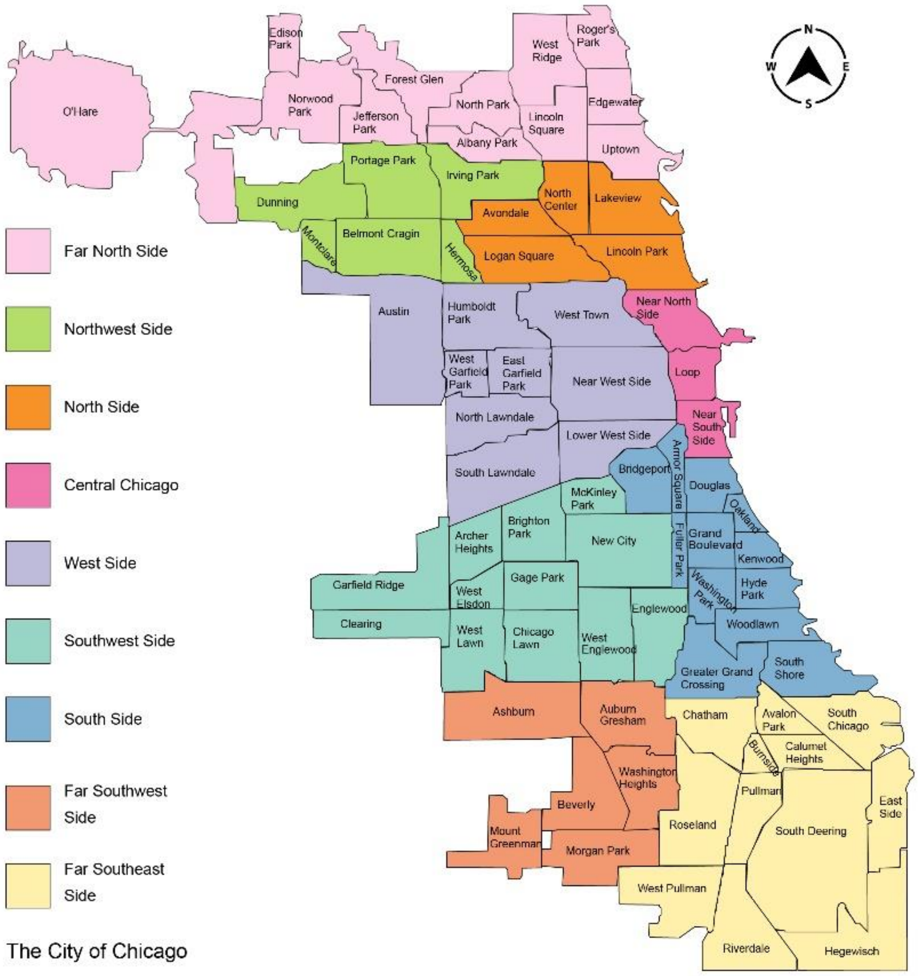


Figure 1. Chicago neighborhood maps. Adapted from Wiki commons.

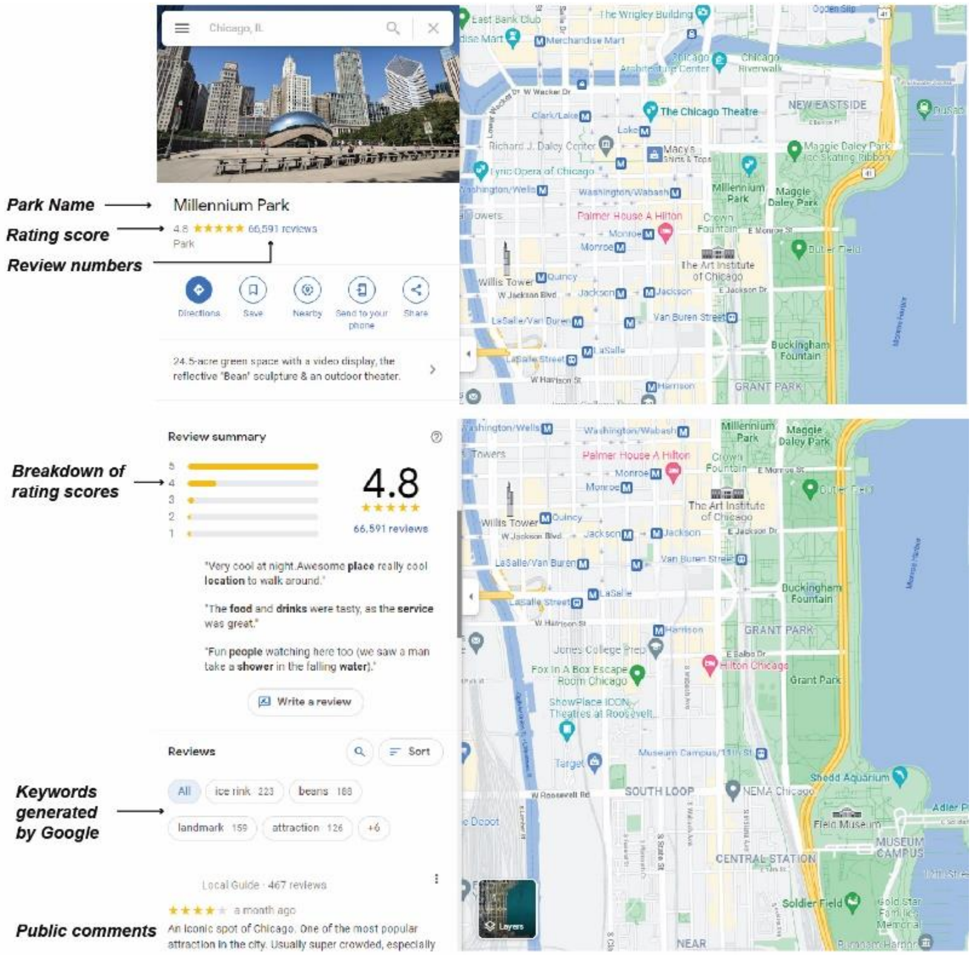


Figure 2. Google Map Reviews interface example.

2.2. Data Collection

As a web-mapping service, user-generated reviews from Google Maps have previously been used to analyze customer perceptions of theme parks, restaurants, and libraries [39,40]. We suggest that these reviews may also help understand the spatial patterns and the user experiences of the public parks under study.

There has been a dramatic increase in the number of Google Map reviews received since 2015 as compared with other review platforms [41]. Pertinent to this research, when compared with other platforms such as Yelp or TripAdvisor, Google Maps also received more reviews for public parks, especially for community parks that are relatively small, providing inclusive information and samples for further analysis.

We retrieved records of 605 public parks in Chicago through Google Maps Application Programming Interface (API). Based on the names and addresses of the public parks from the Chicago Park District website (https://www.chicagoparkdistrict.com/ (accessed on 6 July 2021)), as illustrated in Table 1, we collected the park attributes, geolocations, park ratings, as well as the frequency and the content of reviews for each park up from the beginning time that the review is available to August 2021. The collected attributes of the public parks were further converted into spatial points with their corresponding structural and non-spatial information in the Environmental Systems Research Institute (ESRI) Shapefile format. We further extracted keywords of the collected reviews for each individual park along with the total number of reviewers who mentioned the keywords in their reviews (Table 2).

Table 1. Park information collected through the Google Maps API.

Attributes	Description
name	Park name.
formatted_address	A string containing the human-readable address of this park.
place_id	A unique identifier of this park, which can be used with other Google APIs.
rating	Park rating, from 1.0 to 5.0, based on aggregated user reviews.
user_ratings_total	The total number of reviews of this park, with or without text.
lat	Latitude of this park in decimal degrees.
lng	Longitude of this park in decimal degrees.
url	The URL (Uniform Resource Locator) of the official Google page for this park. This is the Google-owned page that contains the best available information about the place.

Table 2. Key words from the Google Maps Reviews.

Attributes	Description
place_id	A unique identifier of this park, which can be used with other Google APIs.
key_words	Key words mentioned by multiple reviews that can label the features of a park.
Kw_mentioned	Total number of each keyword for all reviews.

To explore the relationship between the pattern of public park distribution and the socioeconomic conditions of the surrounding communities, we also collected the 2019 household income information of Chicago residents at the census tract level (https://datausa.io/profile/geo/chicago-il (accessed on 6 July 2021)), 100 m gridded population structure data in 2020 from WorldPop (https://www.worldpop.org/ (accessed on 6 July 2021)), 38 m human settlement history layer showing the presence of built-up in different epochs [42], and the human modification layer in 2016 which shows the percentage of human activities, such as urban infrastructure, agriculture, mining, or transportation, in each 1 km pixel [43]. We further summarized the map of the percentage of children under the age of 15 from the WorldPop population structure data.

2.3. Methods

2.3.1. Web Crawler and Web Content Parsing

The web crawler, also known as a spider [44] or an automatic indexer [45], is a powerful technology that collects data from web sources by iteratively extracting web contents from a list of URLs, which are also called seeds. In our data collection process, the URLs for all parks shown in Table 1 are considered as the seeds of the web crawler and corresponding web pages are stored by accessing these seeds. Since web pages are built using text-based mark-up languages (HTML and XHTML), with data distributed in the contents, same class information is typically encoded into similar pages by a common script or pattern. After crawling the web pages, we identified and scraped web elements with the targeting information using the Selenium package in Python. All data stored in web elements found by Selenium were saved and cleaned using regular expression [46] to remove the redundant and noisy records. Figure 3 shows a subset of the data collected and cleaned:

place_id	key_words
ChIJvX8aF-ElDogRws8sWkRmL60	All kids:18 house:9 play:8 walk:8 pool:5 basketball:5 peaceful:4 community:3 baseball:3 restaurants:3
ChIJqXs7PlckDogRS2CeQDq4BAY	All kids:18 play:6 basketball:6 football:4 swimming:4 house:3
ChIJb2Z0dB_TD4gRIOp_StKNk80	All sandbox:15 splash pad:11 toddler:8 swings:6 clean:6 water feature:5 structures:3 parents:3 slides:3 benches:3
ChIJOeKUdVMrDogRmMZVEmCCSdE	All beach:10 walk:6 benches:5 lake:4 trees:4 bike path:3 water:3

Figure 3. A subset of the collected and cleaned data. The left column represents the unique park identifier and the right column contains the key word information.

2.3.2. Kernel Density Estimation

As an important nonparametric technique in statistical analysis, kernel density estimation (KDE) is used to estimate the probability density function of a random variable [47]. Kernel density estimation has been widely used for multiple purposes such as spatial data smoothing, hot spot detection, and risk prediction [48–50]. When dealing with geospatial information, KDE generates a density surface where each cell is rendered based on the kernel density at the pixel center. For each observed geographic point, KDE fit a kernel function, assuming that each observation is continuously spread within its kernel window. Given by n observed points p_i, the predicted density $\rho(x)$ at a new location x is determined by the following formula:

$$\rho(x) = \frac{1}{r^2} \sum_{i=1}^{n} \frac{3}{\pi} pop(p_i) \left(1 - \left(\frac{dist(p_i, x)}{r} \right)^2 \right)^2, \; for\ dist(p_i, x) < r \tag{1}$$

where r represents the search radius, function $pop(p_i)$ represents the population field, which serves as the weight on each observation, and $dist(p_i, x)$ computes the distance from each location x to the observation p_i.

Following Equation (1) above, we further generated the equally weighted kernel density map in ArcGIS Pro to show the spatial pattern of the public park distribution in Chicago, with each pixel on the resulting image indicating the number of public parks per square meter.

2.3.3. Global Moran's I and Getis–Ord Gi* Statistics

To understand the spatial patterns and to validate the significance of the park ratings and of the number of ratings of the different parks reviewed, we conducted spatial autocorrelation analysis and calculated both the global Moran's I and Getis–Ord Gi*. In general, Moran's I compares the similarity of the value at the current location with its adjacent locations [51]. Getis–Ord G* identifies spatial clusters where high or low values are observed [52].

We used global Moran's I to measure the spatial autocorrelation among ratings and the number of ratings received for each park based on its location and the value simultaneously. This spatial autocorrelation analysis measures the overall pattern of the Chicago public park distribution, which ranges from clustered, random, to dispersed [53]. The Moran's I statistic for spatial autocorrelation is calculated as:

$$I = \frac{n}{S_0} \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{i,j} (x_i - \mu)(x_j - \mu)}{\sum_{i=1}^{n} (x_i - \mu)^2} \tag{2}$$

where x_i is the value of the observation i, n is the number of the observations, μ is the mean of the observation, w_{ij} represents the spatial weight between i and j, and S_0 is the aggregate of all weights.

A large and positive Moran's I indicates a high similarity between the parks and their adjacent parks in terms of the rating or number of ratings received, and a negative value represents the dissimilarity when compared with adjacent parks.

The Getis–Ord Gi* Statistic evaluates the significance of local pattern and clusters of public parks [54,55]. By testing each park within the context of neighboring features, Getis–Ord Gi* identifies the clusters. An observation with a high value and surrounded by high-value points can be called a statistically significant hot spot and can be identified by the Getis–Ord Gi* statistic. The Getis–Ord Gi* can be calculated as following:

$$G_i^* = \frac{\sum_{j=1}^{n} w_{i,j}x_j - \sum_{j=1}^{n} w_{i,j}x_i}{S\sqrt{\frac{n\sum_{j=1}^{n} w_{i,j}^2 - \left(\sum_{j=1}^{n} w_{i,j}\right)^2}{n-1}}} \tag{3}$$

where x_i is the value of the observation i, n is the number of the observations, w_{ij} represents the spatial weight between i and j, and S is calculated as

$$S = \sqrt{\frac{\sum_{j=1}^{n} x_j^2}{n} - \left(\frac{\sum_{j=1}^{n} x_j}{n}\right)^2} \tag{4}$$

In our analysis, a high value of Getis–Ord Gi* indicates that the total park ratings or the total number of people evaluating parks in the neighborhood is high relative to the average of all public parks in Chicago. Likewise, a negative value indicates a low value cluster and a value approaching to 0 means the intermediate condition.

2.3.4. Review Keywords Analysis

To reduce the dimensionality of the scraped park reviews and explore the features of the public parks in Chicago in terms of management improvement, keywords of park reviews and their corresponding frequency of being mentioned were exploited to explore what features are of most concern to visitors. First, the keyword frequencies for all parks were aggregated together and the top 10 mentioned keywords were visualized to give a big picture of the park features of most concern. Second, we stratified park reviews according to their ratings to illustrate the potential differences in park attributes, conditions, and environments that lead to differences in park ratings. The pie charts of keywords are then generated for parks with ratings ranging from 1 to 2 (1 park), 3 to 4 (22 parks), and 4 to 5 (329 parks) stars (scores). When we scraped the review data, there were no parks in Chicago rated between 2 to 3 stars on Google Maps and some parks do not have reviews. Finally, 6 parks in different geographical locations are manually selected as examples to illustrate differences of features that visitors mentioned.

3. Results and Conclusions

3.1. Spatial Patterns of Public Parks in Chicago

Overall, both park location and the most frequently rated parks are significantly clustered by Lake Michigan, with a densely populated zone of public parks extending from North Side to Far Southeast Side of the city. The spatial patterns seem be controlled by the distance to the urban infrastructure, local socioeconomic conditions, and park users' behaviors. Figure 4 shows the kernel density map of the public parks in Chicago. Central Chicago and west of the West Side have the most observed dense park distribution in the city.

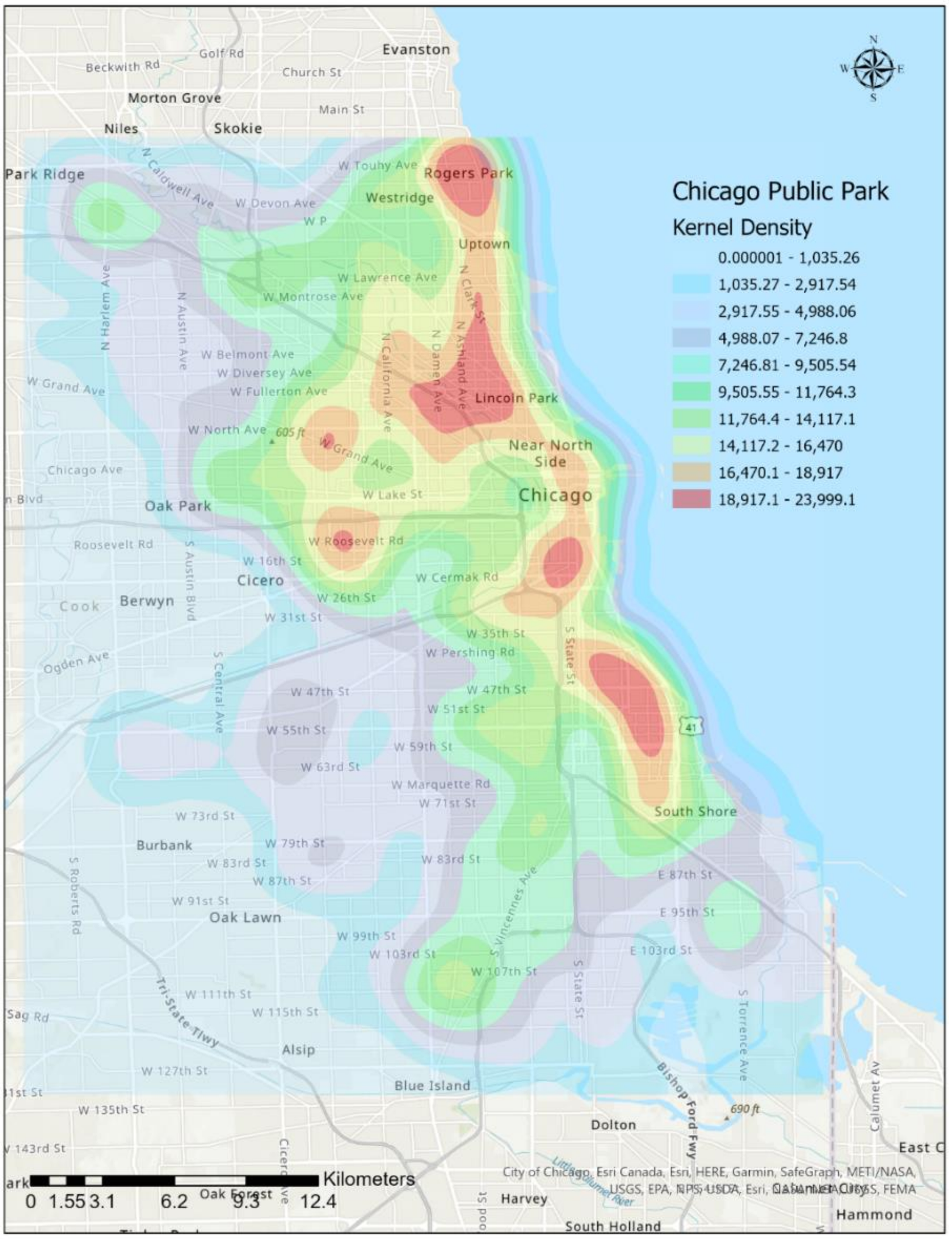


Figure 4. Kernel density map of public parks in Chicago.

The results of the spatial autocorrelation analysis indicate the patterns of park ratings and rating numbers at both the global and local scale. In terms of the global spatial autocorrelation, as summarized in Table 3, there are clustered distributed patterns for park ratings and rating numbers for all public parks in Chicago. This finding implies that high-rating parks are located close to each other in space and the most-visited parks are also spatially clustered together. For the patterns of park rating, an extremely high critical score (z-score) of 4.4 and a very small p-value of 0.000011 were received from the statistical test, representing that it is statistically significant and allowing us to reject the null hypothesis that the pattern is randomly distributed. Parks with similar ratings are thus highly clustered across the space and there is less than 1% likelihood that this clustered pattern is a result of random chance. As for the number of reviews made for each park, a z-score of 2.13 and p-value of 0.033 indicates a less than 5% likelihood that this clustered pattern occurred by chance.

Table 3. Global spatial autocorrelation results.

Attributes	Moran's I	z-Score	*p*-Value
Park rating	0.089	4.40	0.000011
Park rating numbers	0.035	2.13	0.033

In terms of the local distribution, the hot and cold spots with respect to the park ratings and rating numbers were detected through the Getis–Ord Gi* statistic. A hot spot on the map represents a cluster of parks with high ratings and a cold spot refers to low-rated parks. We further overlaid the quantified hotspots with the 2019 household income information of Chicago at the census tract level shown as the grayscale color scheme base map in Figure 5, to illustrate the relationship between socioeconomic conditions in the neighborhood and the park rating ranking distribution. The detected hot and cold spots with respect to the park ratings and rating numbers are displayed as red and blue colors, respectively. The identified hot and cold spots measure the relative degree of parks being high or low in park ratings. Across all the public parks in Chicago, there is an average score of 4.36 on Google Maps Reviews, indicating there are a higher proportion of parks falling into a high-score range in visitor perceptions (see Figure 5).

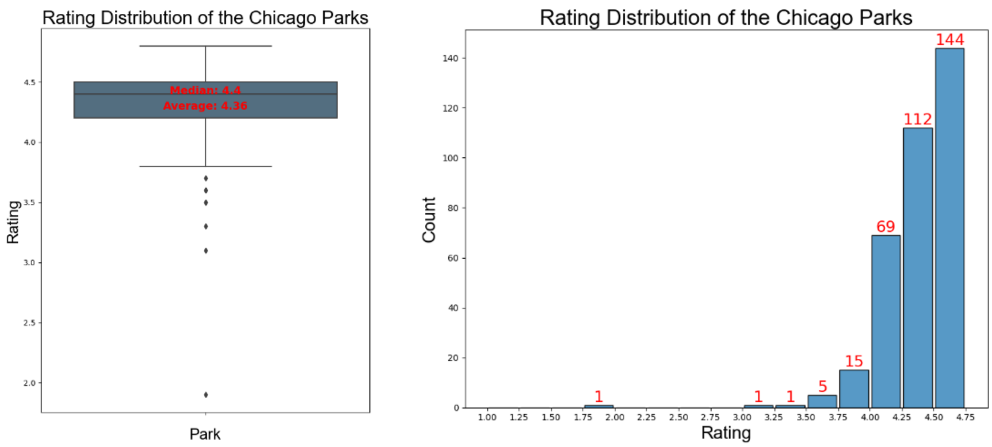
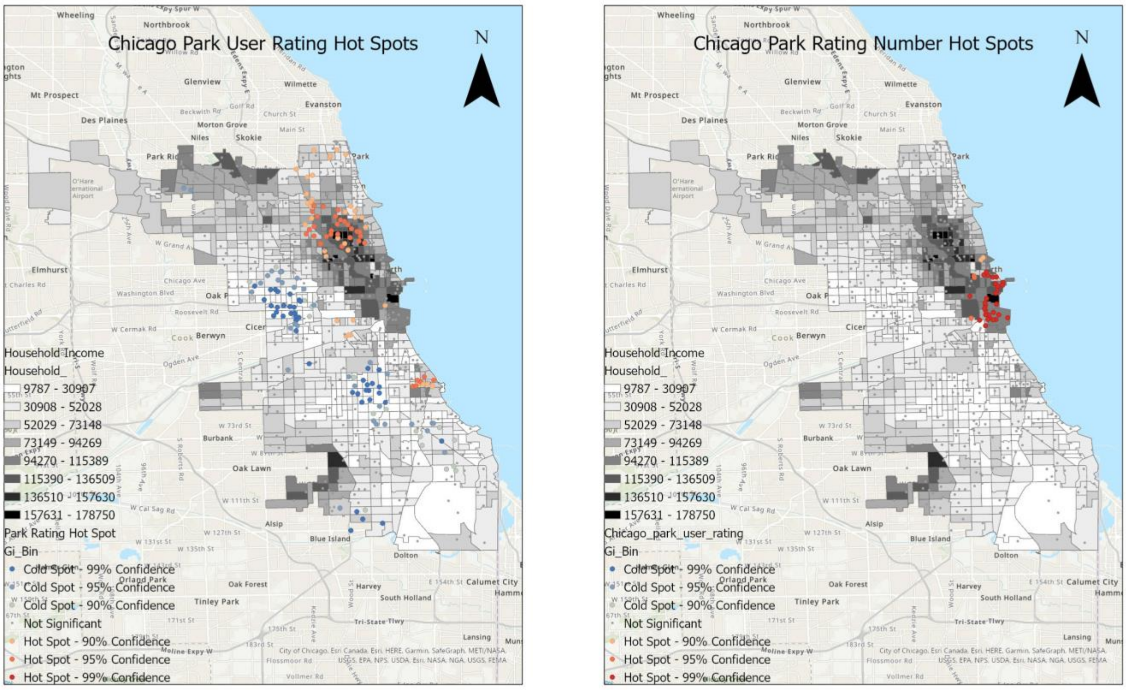


Figure 5. Boxplot and histogram of Chicago parks' ratings.

According to the U.S. census tract household income information, the level of the household income is directly identified in the base map of Figure 6a,b, showing that people with a high level of income (USD 100 k~150 k annually) are more likely to live in several neighborhoods, including Central Chicago, the North Side, the West End of the Far North Side, Hyde Park in the South Side, and several neighborhoods in the Far Southwest Side. As seen in Figure 6a for park rating clusters, which indicate the spatial autocorrelations of park ratings, there are two significant hot clusters of high-rated parks by the Hyde Park area and the North Side, and three significant cold clusters in the inner city, which are in the West Side, and the Southwest Side, and some in the Far Southeast Side. While it is intuitive to assume people live in a neighborhood that has both positively and negatively rated parks, the distribution that we found implies that people living in hot clusters have a much higher possibility of visiting parks that are all highly rated (with parks rated on an average of 4.51 out of 5). On the other hand, people living in the cold clusters are less likely to have opportunities and access to good-quality parks that are found in hot clusters if relying on walking or biking distances, and by virtue of location, are more frequently proximal to parks with low scores (with an average rating of 3.06 and 2.45 respectively out of a 5-score system). A comparison of the average scores among these cluster indicates that, although most parks in Chicago received a relatively high score in this Google rating system, those cold clusters identified from our analysis were still, under common sense, poorly rated online and had a relatively large difference from parks in the cluster of highly rated parks.

The clusters of high-rating score parks on the map also correlate with income levels in obvious way, which reaffirms the environmental justice issues discussed in the Introduction section of this paper. Hence, some of the local socio-economic neighborhoods with lower household incomes have lower quality parks and thus have a reduced chance to reap the benefits of nature, which reaffirm an urban environmental and social injustice issue.



(**a**) (**b**)

Figure 6. The hot and cold spots detected through the Getis–Ord Gi* statistic with respect to the park rating scores (**a**) and rating numbers (**b**). The household income of census tract in 2019 is colored by grayscale.

In terms of the review and rating quantities, as shown Figure 6b, only one hot spot for rating numbers is identified, which is in the downtown area, in the Central Chicago neighborhood close by Lake Michigan. This finding indicates that public parks located in downtown Chicago have been visited and reviewed the most. This makes sense, as they are likely more accessible to greater numbers of people by virtue of their central location, including tourists, who tend to cluster in downtown Chicago to visit its myriad attractions. In addition, the spatial patterns of park rating and rating numbers also indicate that areas with the most visited parks are not necessarily the places with more high-rating parks. The downtown area in Central Chicago seen Figure 6b has a cluster of hot spots of reviews with high statistical confidence but as mentioned above, has one hot spot of high-rating parks on Figure 6a, which means the downtown area has parks with varying levels of ratings. Conversely, neighborhoods with clusters of high- or low-ratings on Figure 6a, for example the neighborhoods in the North Side and the West Side, had no significant hot spots based on the number of reviews on Figure 6b.

We further examine the spatial relationship between the hot spots and cold spots of park ratings with the population, the percentage of children, the percentage of human modification, and the age of the urban built-up, as shown in Figure 7. Overall, clusters of high-rating parks are within the zones of higher populated areas when compared with those clusters of low-rating parks (Figure 7a). Clusters of high-rating parks are also more likely to be in the regions where urban built-ups were constructed before 1975 while most low-rating parks are in urban regions built in between 1975–1990 (Figure 7c). Although there is little difference between the hot and cold spots in terms of their spatial distribution across the maps of child percentage and the degree of human modifications (how much human activity has changed the wilderness), all of these park clusters are within regions where there are higher percentages of children and higher human modification than all other parks that are sparsely distributed (Figure 7b,d).

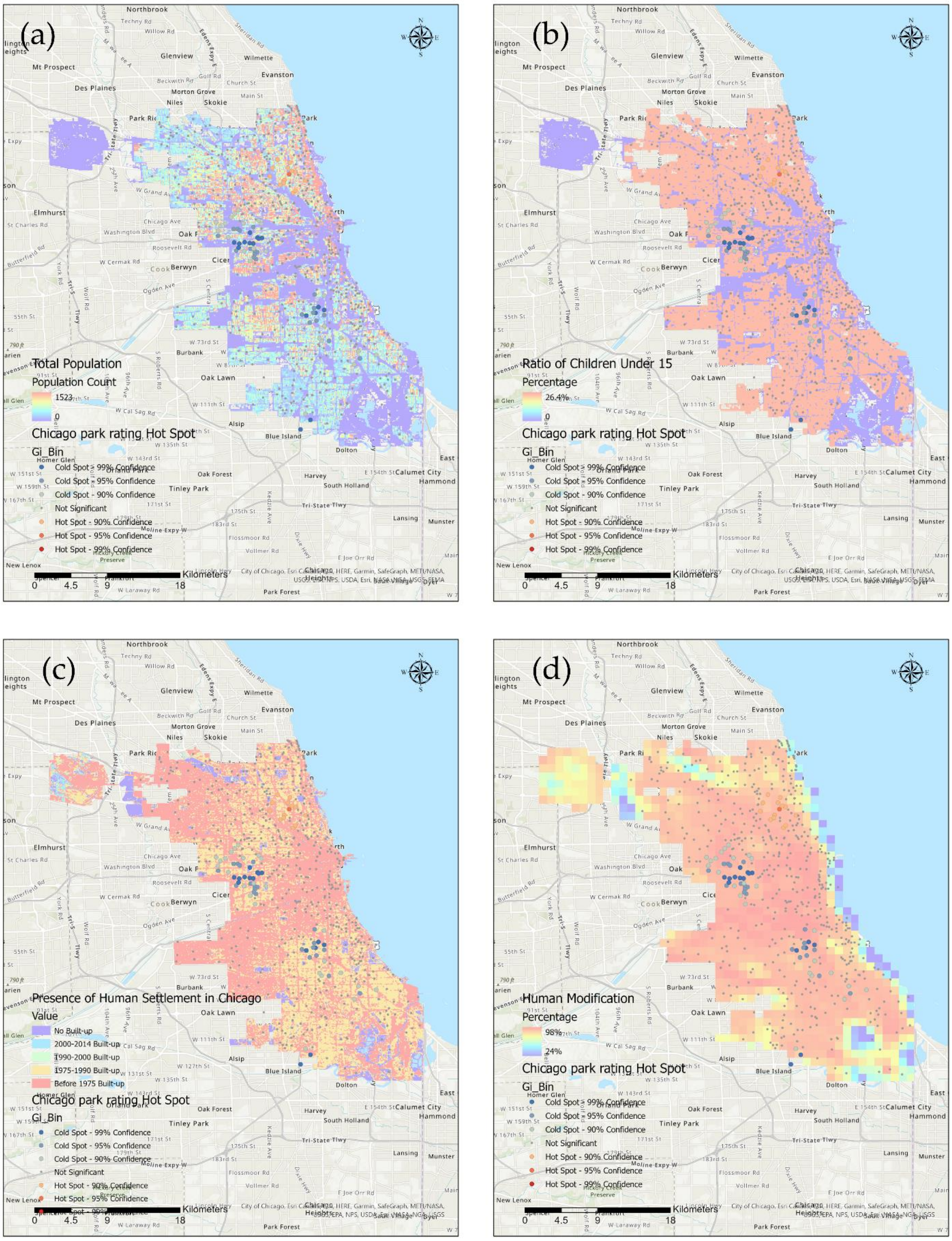


Figure 7. Maps of the relationship between park ratings of Chicago and the spatial patterns of (**a**) the total population of Chicago, (**b**) the percentage of children in the population who are under 15 years old, (**c**) the epoch (before 1975, from 1975–1990, from 1990–2000, and from 2000–2014) of presence of the human built-up, and (**d**) the percentage of human modification (how much human activity has changed the wilderness).

3.2. Keywords of Park Reviews by Different Ratings

As shown in previous figures, the review content can be categorized by its rating scores, and further analysis can be done to understand the reasons behind higher or lower reviews. To develop the overall picture of the park characteristics, the top 10 most-mentioned keywords with respect to frequency are visualized in Figure 8. Referencing Figure 9, the pie charts of the keywords were generated for parks with the star ratings ranging from 1–2 (low-rating), 3–4 (medium-rating), and 4–5 (high-rating). Although there are more parks falling into the star rating range of 4–5 and fewer in the range of 1–2, we still use these numeric splits instead of the relative values of even splits based on the differences of park ratings, to partition the keywords of the parks, in order to better simulate the actual opinion of park users under the general intuition that a high rating represents a good quality while a low rating implies dissatisfaction from previous visitors. The larger slice of the pie chart represents a higher frequency of the word mentioned by park reviewers.

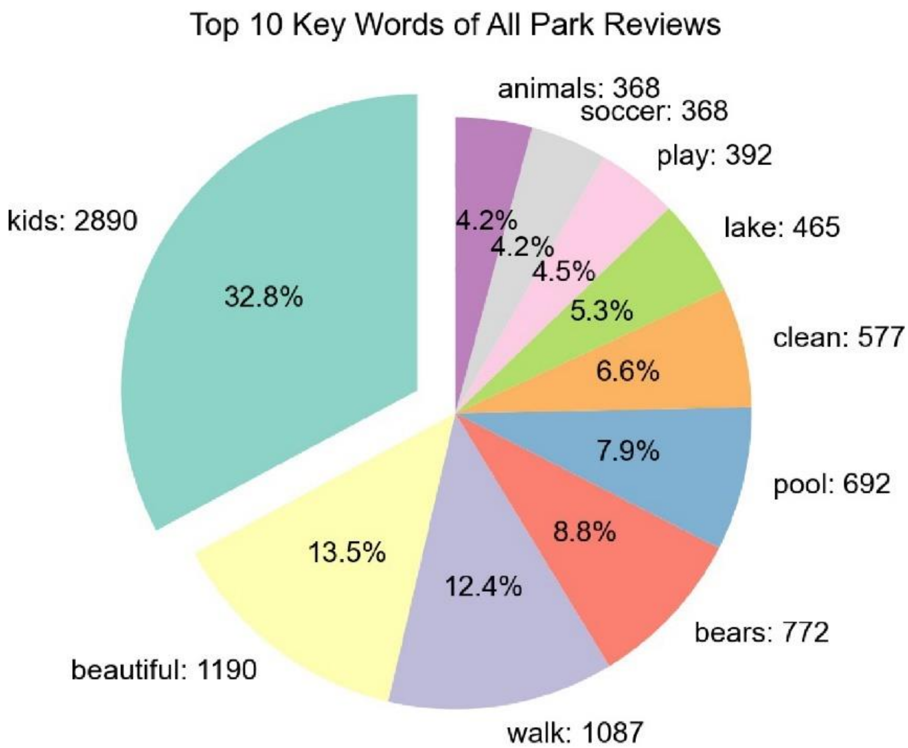


Figure 8. Pie chart of the top 10 park reviews: keywords frequency for all parks.

Results of the pie charts indicate that one park may be poorly perceived or unappreciated by users because it might be occupied by people who are unhoused and have an abundance of trash. Overall, 'homeless people' and 'bottles' are the two keywords degrading the rating of a park while 'kids', 'beautiful', and 'walk' are the three most-received keywords for high-rating parks. People might rate a park as average due to a mix of positive reasons, such as children's play equipment, sport fields and courts, and negative reasons, such as gang occupancy and the presence of people who are unhoused. We also identified more sports-related keywords such as ball game, courts, pool, and gym for the medium-rating parks than the high-rating parks. As for high-rating reviews, people used words such as beautiful and clean to describe the characteristics of the park, and used keywords such as animals they see, soccer, play, animals, beach, walk to indicate their favorite activities in the park. Many of the high rating key words were related to nature and the park amenities it provides. Park users might view these qualities as health-promoting environments.

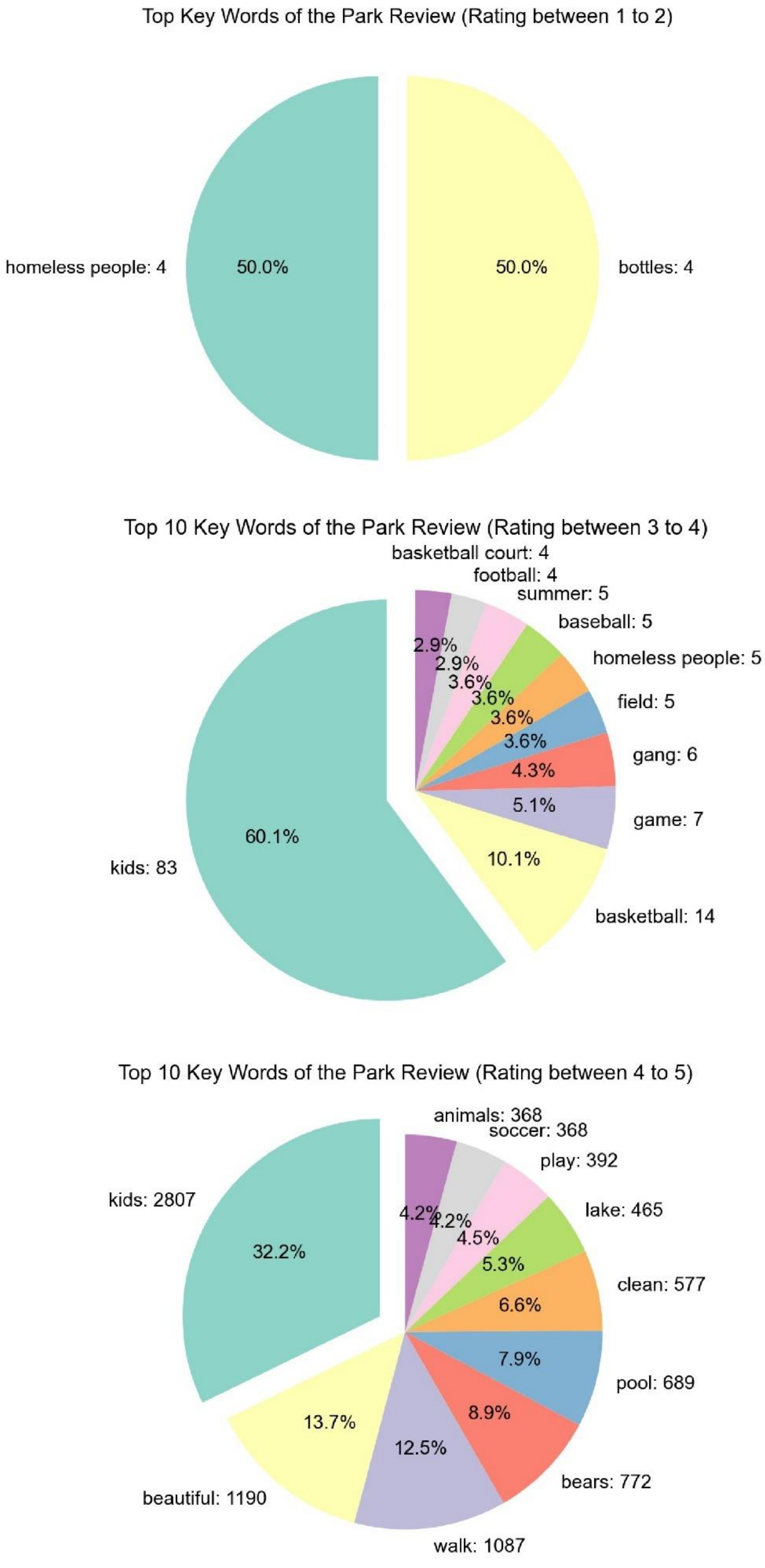


Figure 9. Pie charts of the park review keywords frequency by different ratings. From top to bottom: rating 1 to 2, rating 3 to 4, and rating 4 to 5.

In addition to the overall keyword distribution of the entire research area, six evenly distributed parks through Chicago (Burnham Park, Grant Park, Horner (Henry) Park, Marquette (Jacques) Park, McKinley (William) Park, and South Shore Cultural Center) were manually selected to explore the park features and characteristics for a more detailed analysis and individual park comparison. As shown in Figure 10, three parks are along Michigan Lake (Burnham Park, Grant Park, and South Shore Cultural Center), and three parks (Horner (Henry) Park, Marquette (Jacques) Park, and McKinley (William) Park) are located inland. We generated 6 pie charts of the top 5 mentioned keywords respectively for each park in Figure 11 to show the frequency and proportion of different types of feedbacks from visitors.

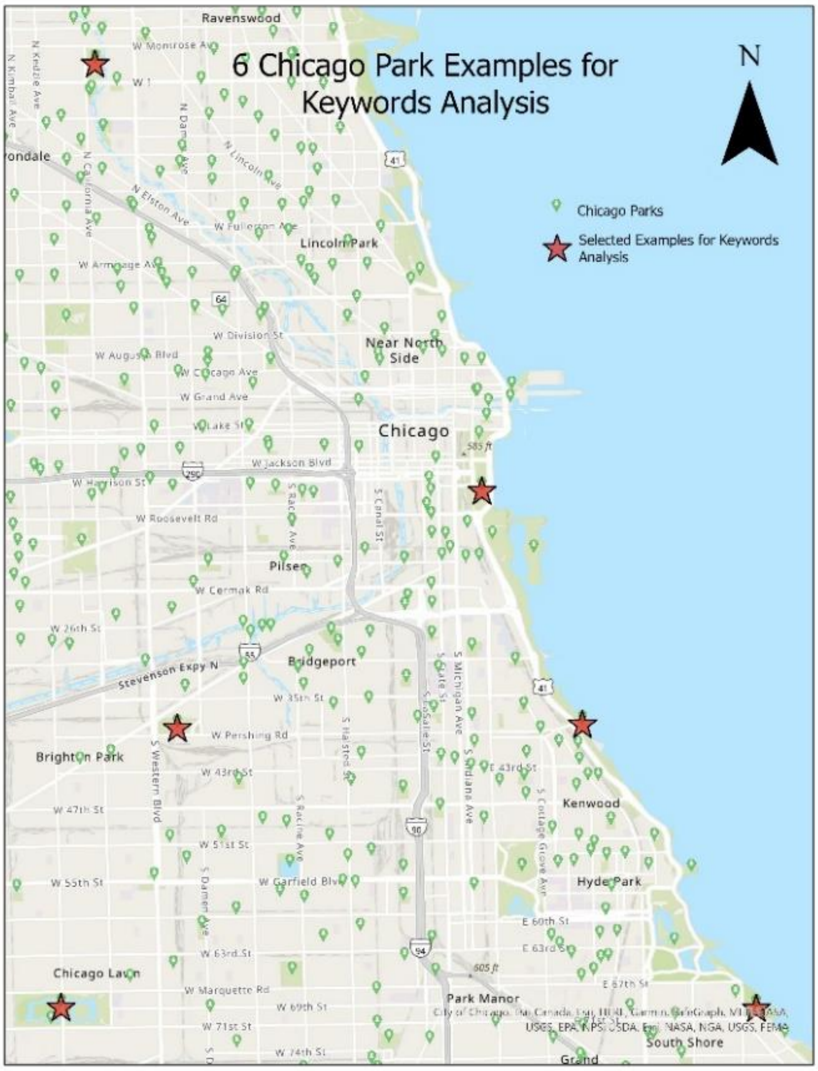


Figure 10. Distribution of 6 manually selected parks for keywords analysis.

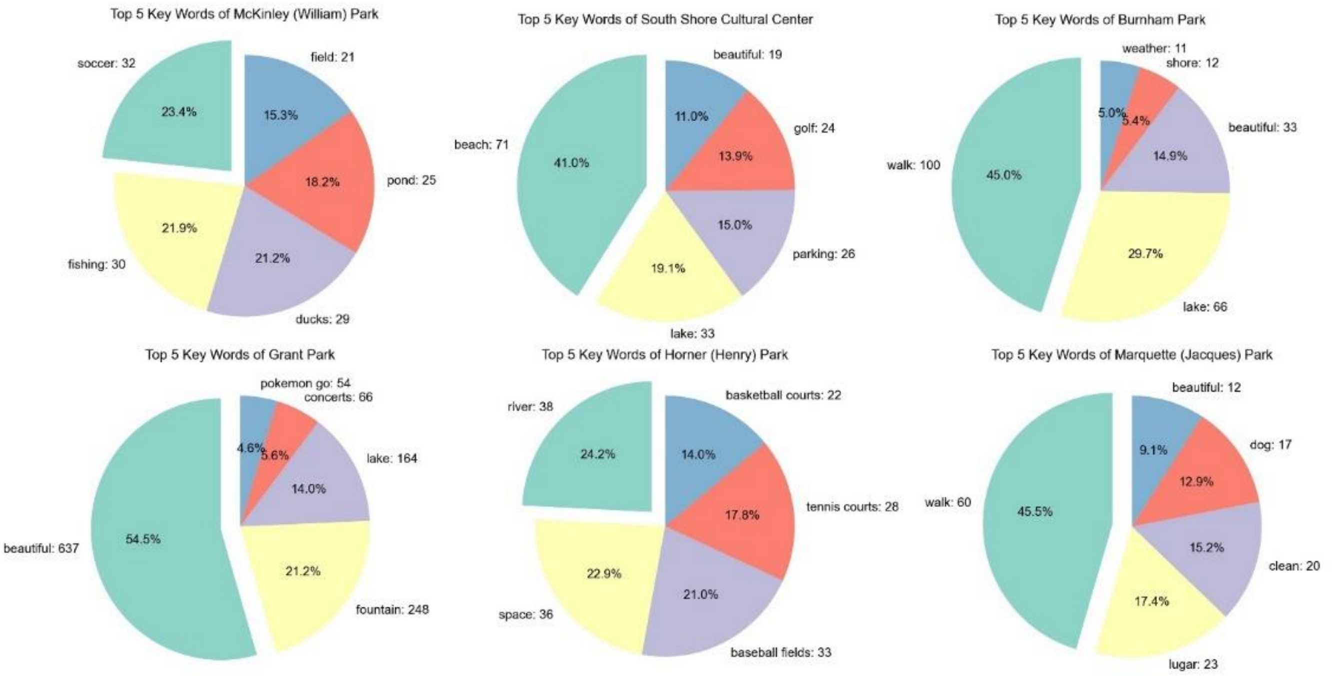


Figure 11. Pie charts of 6 selected parks for keywords analysis.

These pie charts demonstrate that each park has provided dramatically different features that attract visitors. For example, Grant parks have six features that share similar weights, including soccer (activities), fishing, field, pond, and ducks. People prize their visits to Burnham Park mostly because of its walking experience, its lake, and its beautiful view. Users like Horner (Henry) Park due to its river, space, and its basketball court, tennis court, and baseball fields. This keywords analysis would demonstrate a rough but bold picture of different parks, and almost provide a short summary of the characteristics of each park.

4. Discussion and Conclusions

As shown by the Chicago public parks Google Maps reviews, if well-utilized and effectively monitored, they can be a valuable tool to be integrated into the current city park system management. To respond to the previously mentioned challenges that parks and recreation departments are facing, Google Map reviews have several characteristics that are complementary to existing evaluation frameworks and strategies mentioned in the Introduction:

(a) The evaluation and commenting are continuously live; hence, the information is always up to date.

According to Google Product Director Russell, various channels are available for people, business owners and consumers, and others to update map data and leave comments. Google reviews of public parks are updated instantly, every time a visitor submits a response and Google Maps is also updated constantly [56]. Therefore, parks and recreation administrators have the capability to monitor users' perception of the parks by simply reviewing comments and monitoring the most recent scores of all city parks. What is invaluable is that no additional effort is required to distribute surveys and analyze the results, the feedback portal is always open, and the information is always current.

(b) Social media, especially Google Maps, is far-reaching, allowing any community members to contribute.

Social media is widely used worldwide; hence, in terms of accessibility, social media has the potential to become the most far-reaching and participatory tool in research. According to the Pew Research Center's report on social media usage from 2005 to 2015, 65% of adults use social networking sites [57]. In terms of the social disparities aforementioned in discussion of survey participation, low-income families are consistently under- sampled in traditional methods [14]. Individuals with a higher level of education and higher household income still lead the way, but more than half (56%) of the lowest income household residents use social media. Race and ethnicity are another impacting factor when public hearings and design charettes are the methods used. Yet, according to the Pew Center's research, there is no notable difference between racial or ethnic groups who used social media, with whites, Hispanics, and African Americans having 65%, 65%, and 56% use respectively [57]. We are not saying that all people who use social media will contribute to Google reviews; however, in terms of accessibility, it may be easier to leave comments on social media than physically participating in a public workshop, or submitting another online survey. People, regardless of their social status, post their opinions on Google Reviews, when they have positive and negative feelings towards parks, if they have a cellphone and Internet access. If the technology part can be bridged, Google Review has potential to become a more far-reaching opinion gathering tool than any other applications or digital survey tools.

(c) Social media data reveals and support discoveries of environmental justice issues.

The research findings shown in Figures 6 and 7 illustrate the relationships between highly rated parks, poorly rated parks, household incomes, population densities, and level of urban development. Though only one example and one aspect, this indicates the possibility of integrating social media data to show systematic environmental injustice issues in more spectra. Echoing with previous research that the analyses of park quality could inform planning decisions [17], UGC offers an alternative way to get an overarching visitors' perception of park qualities. The method utilized in Figure 9 demonstrates the qualitative potential to roughly exhibit issue keywords for researchers and data collecting staff to start with. However, due to UGC's incomplete nature, the comprehensive factors behind environmental justice issues and limited park usage from particular groups require other types of research, such as focus groups, interviews, and participatory action research.

(d) With thorough and professional analysis, social media records and results may even guide a city's finance and renovation priorities.

Figures 6 and 7 gave park managing staff a quick sketch of the general public's perceptions on what they like and where the parks need to be renovated. Currently, Google Review has not been widely used in the field, and the present results are not close to comprehensive or detailed. However, suppose a park district utilizes a similar UGC component in the future to solicit and encourage residents and visitors to actively offer feedback on the maintenance and status quo of all city parks. In that case, it may reveal which parks currently attract social problems, what problems they are, and how the city can improve those conditions. With the help of social media, even for cities having more than 600 parks to maintain, the findings in Figure 6 offers clear guidance on where poorly rated parks are located and the neighborhoods that need more financial investment to improve people's well-being and daily recreational opportunities. Park and recreation administrators can then use the information to identify concentrated poorly rated parks and invest money and social capital to improve them.

It must be acknowledged that, like other UGC, Google Maps review data has its limitations and cannot be a sole source of information for park and recreation management. That said, some interesting characteristics we examined are:

(1) Reviews, and sometimes rating scores, tend to be polarized.

Research has found that social media is related to political polarization and disinformation [58]. In this project, we found the reviews to be polarized. People tended to leave comments that are either extremely positive or extremely negative. For example, in one of the parks with 2649 valid comments, 1647 comments are associated with a rating of 5/5 scores, 564 comments rated 4/5, 249 comments rated 3/5, 71 comments rated 2/5, and 112 comments rated 1 out of 5. In this case, the scores are not polarized. However, the associated comment lengths can be greater when there are scores of 5 or 1. People tend to share more when they have more to comment about, which is also one of the characteristics of participating in social media.

(2) Data mining and scaping can be tedious and require professional skills and training.

Social media has characteristics like unstructured data, is subjective, and must be solicited from a massive database. To use the data correctly and effectively, more than one research method is needed, such that extraction, coding, content analysis, and identifying relationships and statistical cluster analysis are essential [59]. This requires that those who handle the data have enough training and experience to make the data useful. It also requires other research team members to have additional eyes on data to make sure that the analytical procedures are ethical, and that the data responds to the clear objectives of the research. These criteria might be challenging for park and recreation departments; however, this encourages forging a collaboration of park and recreation departments with research institutions or local universities.

(3) Review quantities are key to convincing results. For parks with less comments, there is greater potential for biased results.

Social media data and big data also has "noise," which include advertisements, marketing messages, robot-produced content, and/or non-relevant conversations. Some social media have over 70% non-relevant or noise message content [60]. Hence, there needs to be a large enough sample of reviews to reduce bias and increase objectivity. In this research, the noise was between 20–40%, leading to a park with 600 reviews generating less than 400 reviews to work with. To expand the effectiveness of social media research about park usage, extra effort is needed to ensure widespread, effective participation of park users. Moreover, reviewers' identity is difficult to identify, which may lead to false calculations or false results of the research.

(4) Reporting bias still exists.

Though social media is far reaching and include more information and reach a wider community than those who typically could participate in a community workshop, UGC still has its natural reporting bias. Online reviews are inherently incomplete since they would not capture the opinions of those who do not have access to internet, or who do not leave their comments or write a review [61]. However, in some cases, these biases can be eliminated by different strategies. As an example, research finds that people tend to leave comments when they are satisfied compared to unsatisfied, suggesting that the bias can be rectified by an inverse probability weighting approach [61]. Moreover, UGC can be combined with other research methods, such as traditional sociological methods including interviews and focus groups, and participatory methods, to retrieve additional data from particular populations who are underrepresented in the world of social media.

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