EXPLORING THE ATTRACTION OF FLOWERS IN URBAN PARKS IN SHANGHAI: AN ANALYSIS OF FLOWER-RELATED SOCIAL MEDIA DATA

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Abstract. Flowers play a significant role in urban parks, yet their impact on visitor attraction remains underexplored. In this study, 14 parks in Shanghai were selected as research sites, and a social media data analysis model was established using data from the Weibo platform. The model includes data collection, cleaning, extraction, and analysis to assess the attractiveness of flowers to park visitors. The key findings are as follows: (1) Based on flower-related data, parks can be categorized into single-peak, double-peak, and multi-peak types. (2) Trends in overall and flower-related social media data generally align, although overall social media data often exhibits sharper peaks. (3) Fluctuations in the proportion of flower-related data vary across different time scales. Over longer periods, the proportion correlates with the flowering seasons, while on shorter time scales, it may contrast with overall data trends. (4) A comprehensive strategy that emphasizes signature flowers while promoting floral diversity is recommended to maximize visitor engagement and maintain year-round ecological balance.
Keywords: *park visitation, seasonal trends, social media, peak analysis, flower attraction*

Introduction

Cherry blossoms (*Prunus serrulata*) in spring and lotus flowers (*Nelumbo nucifera*) in summer consistently attract numerous park visitors. Selecting suitable flower species and organizing flower-themed activities are crucial for attracting visitors, enhancing their experience, and planning or designing new parks (McEwan et al., 2020). This requires understanding the factors that attract visitors to urban parks and the ways flowers influence their behavior.

Research indicates that the distance between urban parks and residential areas (Moran et al., 2020), design layout (Jeon and Hong, 2015), biodiversity (Gonçalves et al., 2021), landscape planning (Zhu et al., 2021), recreational facilities, and safety factors (Han et al., 2018) are key factors attracting visitors, with the appeal of flowers categorized under biodiversity and landscape planning. A positive relationship exists between flowers in urban parks and visitors. First, flowers enhance the aesthetic appeal of parks, and during blooming seasons, they attract more visitors (Moran et al., 2020). Second, flowers increase biodiversity, attracting nature lovers and photographers more frequently (Serée et al., 2023). Third, exposure to natural landscapes reduces stress and improves mental health, encouraging more visits to parks (Meyer-Grandbastien et al., 2020). Many urban parks collaborate with communities to plant and maintain flowers, enhancing resident participation and increasing the park's attractiveness (Tan et al., 2021). These factors demonstrate how flowers in urban parks attract visitors.

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Traditional research methods, including questionnaires (Gidlöf-Gunnarsson and Öhrström, 2007), interviews (Veitch et al., 2006), and observation of user behavior (Lo and Jim, 2010) employ conventional analysis techniques. However, these methods face several challenges. Traditional methods are very time-consuming and prone to observer effects and social desirability bias (Brownson et al., 2009). In data processing, traditional analytical methods struggle with efficiency and precision in large-scale, heterogeneous data analysis (Morency, 2008). They also have difficulty processing various data types, such as text, images, and videos, and cannot capture users' behaviors in real time (Patel et al., 2009).

Social media and Natural Language Processing (NLP) technologies can solve these problems to some extent. Social media users are willing to share their opinions, behaviors, and emotions, generating a large amount of high-quality data (Niu and Silva, 2020). This data can reflect users' genuine intentions and preferences (Wan et al., 2021). Large amounts of data can be extracted from social media through web scraping and NLP technologies with high relevance and accuracy. These systems can process large-scale data at high speed, identify existing patterns and trends, and thus provide insights of profound value (Azzaoui et al., 2021).

Some earlier studies have integrated social media data into the analysis of flower appeal in urban parks by using the number of social media posts as a proxy for flower appeal. The existing literature has identified flowers that attract visitors and further analyzed changes in visitor numbers, park types, and popular flowers (Mou et al., 2023) However, the appeal of parks to visitors is multi-faceted, and the total number of visitors alone cannot fully reflect the appeal of flowers to them. This study focuses on the aspect of flowers, using NLP techniques in data analytics. We collect flower-related data, denoted as A_F to design an evaluation metric, P, representing the proportion of flower-related content. This enables a quantitative analysis to describe the extent to which flowers attract visitors to parks. Further, we visualize word clouds to represent the most popular flowers in a park and use Sankey diagrams to illustrate the correspondence between parks and flowers.

This paper makes the following contributions:

(1) Development of a social media data analytics model: This model encompasses various aspects, including data collection, cleaning, extraction, and analysis.

(2) Definition of metrics for measuring flower appeal: Monitoring the total volume of social media data (A_T) and the volume of flower-related data (A_F), and using these metrics to define the proportion of flower-related data (P).

(3) Text analytics for park-flower correlation: Using text analytics to map the relationship between parks and the flowers that attract visitors.

Method

Study area and urban park selection

Shanghai is one of the most significant cities in China, serving both as a global financial hub and a major tourist destination (Chen et al., 2023). This study focuses on 14 urban parks in Shanghai, selected due to their high visitor traffic and rich floral diversity. These parks include Gucun Park, Shanghai Botanical Garden, Gongqing Forest Park, among others. Their selection was based on their popularity and the variety of flowers they host, which significantly enhances their attractiveness during peak blooming seasons. The study area and urban parks are illustrated in *Fig. 1*.

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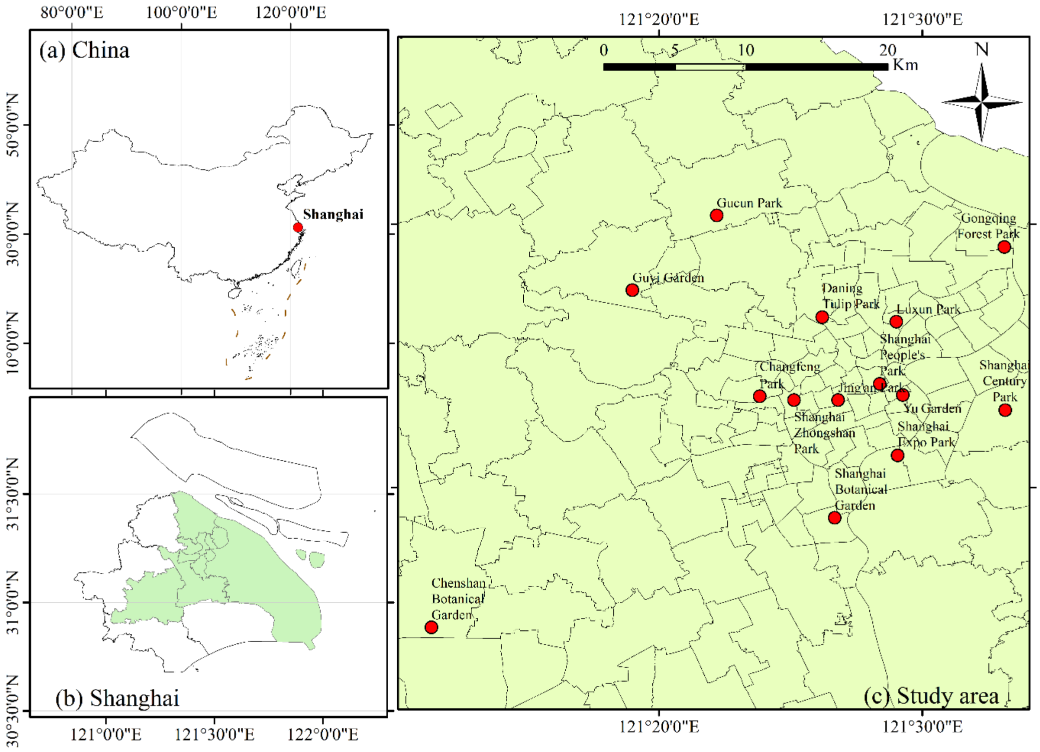

Figure 1. *Study area and urban parks*

The primary ornamental plants featured in these parks include cherry blossoms, peach blossoms (*Prunus persica*), magnolias (Magnolia spp.), and lotuses, among others. Each of these species has distinct blooming periods, which attract large numbers of visitors (Mao et al., 2020).

To deepen the analysis of flowers' influence on park visitation, this study selected Shanghai Happy Valley as a comparative non-park outdoor recreational venue (NPORV). Shanghai Happy Valley is a popular outdoor leisure destination lacking floral elements (Bartold and Kluczek, 2023). By comparing visitor numbers at this venue with those at parks, this research can assess the attractiveness of outdoor recreational sites without floral features, further highlighting the role flowers play in attracting visitors to parks.

Research roadmap

In this paper, a model is proposed that uses social media data to analyze the attractiveness of flowers in attracting visitors to urban parks. The model consists of four parts: data collection, data cleaning, data extraction, and data analysis. The research roadmap is illustrated in *Fig. 2*.

Data collection

The data were collected from Sina Weibo, one of the most popular social networks in China, using a Python-based web crawler. First, the Requests library was used to send HTTP requests to the target pages, followed by Beautiful Soup. Subsequently, Beautiful Soup was employed to parse the HTML and precisely extract the data (Oliveira et al., 2022). For dynamically generated content and sections requiring user interaction, Selenium was used to simulate browser actions (Guardia and Koeva, 2023). When setting

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up the web crawler, we specified certain keywords and time ranges, focusing on the names of 14 parks in Shanghai, as well as Shanghai Happy Valley. The data collection covered Weibo posts from January 1, 2014, to December 31, 2023. The collected data were saved in CSV format, named after the search keywords, and the output structured CSV file contained user-generated content, including user IDs, locations, timestamps, and the text content of each post.

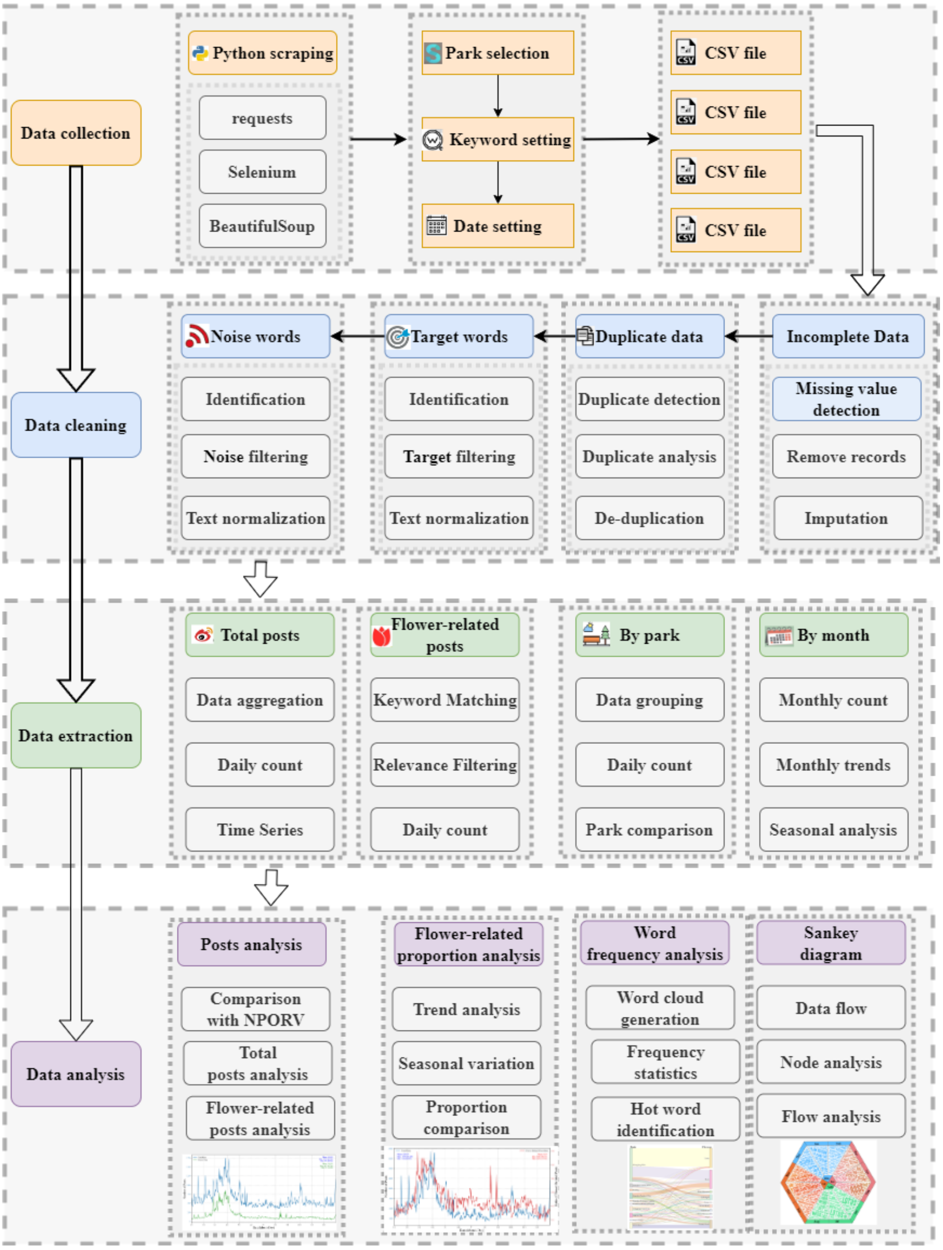

***Figure 2.** Research roadmap*

Data cleaning

We used Python and Pandas to clean the data, focusing on four key tasks: handling missing data, removing duplicates, identifying target words, and filtering noise words (Lee et al., 2023).

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To handle missing data, incomplete Weibo posts were removed, and missing dates were interpolated. Duplicate entries, which were consecutive posts from the same user with identical content, were identified using the duplicated() function and removed with drop_duplicates() function.

We identified target words by comparing the text to a predefined list of keywords, keeping only relevant entries. The text normalization process involved converting all text to lowercase, removing punctuation, filtering out stopwords, and applying stemming. Noise words were eliminated using a predefined list, to ensure consistency and ensure the data was clean and uniform.

Data extraction

After data cleaning, we proceeded to extract the data, handling all posts and flower-related posts separately. For the set of all posts, we compiled data unfiltered for target words, calculated the number of posts per day, and conducted a time series analysis (Thorisdottir et al., 2020). For the flower-related posts, we compiled data filtered by target words, counted the daily post numbers, and performed a time series analysis. Additionally, we organized the data by park for individual park analysis and grouped it by month to analyze monthly trends and seasonal patterns.

Data analysis

In order to better understand how flowers influence the number of visitors and to determine what visitors to the park are interested in at different times of the year, the following data analyses were performed.

• Word cloud analysis of Weibo data: Each month, the monthly Weibo data were summarised and word clouds were generated displaying the main flowers and activities associated with the park for that month, thereby indicating seasonal differences in visitor interests.

• Comparative analysis of visitor attraction between urban parks and NPORV: This analysis compares Weibo discussion volume in urban parks and the NPORV, thereby revealing different visitor attraction dynamics in various seasons as well as holidays.

• Time series decomposition: To analyze the long-term trends and seasonal patterns of A_T, A_F, and P, the time series decomposition method is applied using the additive model. This approach decomposes the data into three main components: trend, seasonal, and residual. The trend component captures and explains the long-term variations in the data, the seasonal component identifies recurring patterns, and the residual component represents random fluctuations or anomalies that cannot be explained by trend and seasonality.

• Comparative analysis of total posts and flower-related posts: By comparing the total daily posts with flower-related posts, this analysis highlights how flowers influence visitation to urban parks across different weather patterns and occasions.

• Correlation analysis: To better analyze the relationship between A_T, A_F, and P, we calculated the Pearson Correlation Coefficient for pairwise comparisons of these three key indicators across 14 parks. The Pearson Correlation Coefficient measures the linear correlation between variables, with a range of [-1, 1], where 1 indicates a perfect positive correlation, -1 indicates a perfect negative correlation, and 0 indicates no correlation.

• Daily total posts and flower-related posts statistics for specific parks: Independent analysis of data from seven selected parks, categorizing and summarizing visitor patterns (single peak, double peak, and multi-peak) will be conducted.

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• Analysis of visitor attention to key flowers and differences in park flower diversity: Using Sankey diagrams, the frequently mentioned flowers and their related urban parks will be shown, helping park managers understand visitor flower preferences, and more effectively allocate resources and promote the brand.

Data overview and data processing

We collected 270,937 Weibo posts from 14 parks in Shanghai between January 1, 2014, and December 31, 2023. As shown, due to Weibo's restrictions, the data volume from 2014 to 2017 is relatively low, whereas the data volume from 2018 to 2023 is more substantial. March has the highest data volume, which is related to spring flower viewing activities.

The format of the collected Weibo data is illustrated in *Table 1*. Each entry comprises User ID, User Location, Time, and Text. For the data of NPORV, the procedures only involved removing invalid data and duplicate data.

Table 1. *Example of Weibo data*

User ID	User location	Time	Text
1727328954	Chenshan Botanical Garden	2014/3/30 22:43	The cherry blossoms at Chenshan are beautiful, the falling blossoms in the rain have a unique charm, and they had a lot of fun
2235200871	Guyi Garden	2021/6/29 15:52	The lotuses in Guyi Garden in Nanxiang bloomed early this summer. Photographers are busy capturing the lotuses in the garden
2397052844	Gucun Park	2021/10/31 15:44	Gucun Park, fragrant osmanthus, green willows, warm autumn

The data volumes after each step are shown in *Table 2*.

Table 2. *Data processing steps and resulting counts for urban park and NPORV*

Data	Urban park	NPORV
Original data	270937	63062
Remove invalid data	260311	59330
Remove duplicate data	257466	58835
Extract target words	66422	N/A
Remove noise words	4548	N/A
Flower related data	61874	N/A

The target words for this analysis are flower names such as cherry blossom, tulip, and lotus, which help in accurately identifying social media content related to flowers. The frequency of mentions for the top 40 flower-related terms in the social media data we collected is presented in *Fig. S1*, which provides an overview of the most recognizable and frequently mentioned flowers by park visitors.

We also identified some irrelevant terms (noise words) to ensure that non-flower-related data is excluded. For instance, while some of these noise words contain the Chinese character '花' (flower), they don't actually refer to flowers, such as '窗花'

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(window decoration) , '葱花' (green onion garnish), '浪花' (wave), and '泪花' (tear). By excluding Weibo data containing these words from our analysis, the accuracy improved by up to 95%, and relevance increased by at least 80%.

Definition of flower-related attraction metrics

By cleaning and extracting data from Weibo posts, we can compute A_T and A_F. A_T represents the total number of visitors, and A_F means the number of visitors who are interested in flowers. To assess the influence of flowers on the allure of urban parks, we have defined the proportion of flower-related data, denoted as P. The formula is as follows:

$$P = \frac{A_F}{A_T} \tag{Eq.1}$$

f A_T is constant, P varies directly with A_F; any variation in A_F will proportionally affect P. Conversely, if A_F remains unchanged, P is inversely related to A_T, meaning that changes in A_T will result in reciprocal changes in P. This correlation provides insights into the critical role flowers play in drawing visitors to urban parks.

Definition of time series decomposition

To analyze the time series of A_T, A_F, and P, the additive model is applied, decomposing the series into trend, seasonal, and residual components to identify long-term trends, periodic patterns, and random fluctuations. The formula is as follows:

$$Y_t = T_t + S_t + R_t \tag{Eq.2}$$

where Y_t is the observed value at time t; T_t represents the trend component, capturing long-term changes; S_t represents the seasonal component, reflecting periodic fluctuations with a cycle length of p; (i.e., $S_t = S_{t+p}$); and R_t represents the residual component, indicating random variations or anomalies.

Results

Tourist attraction: Urban parks vs. NPORV

Urban parks and NPORV are both outdoor leisure venues, but they differ significantly in terms of tourist attraction. Urban parks primarily draw visitors with their natural landscapes, while NPORV attracts crowds through different resources, such as amusement facilities. Due to the differences in their core attractions, the visiting patterns of tourists also differ.

Do flowers attract visitors to urban parks? To address this question, we utilized a consistent methodology to gather Weibo data from Shanghai Happy Valley, covering the period from January 1, 2014, to December 31, 2023, which served as a dataset for NPORV. We then conducted a comparative analysis of the Weibo data from 14 urban parks against that from Shanghai Happy Valley. The daily comparison of the number of Weibo posts related to urban parks and NPORV is illustrated in *Fig. 3*.

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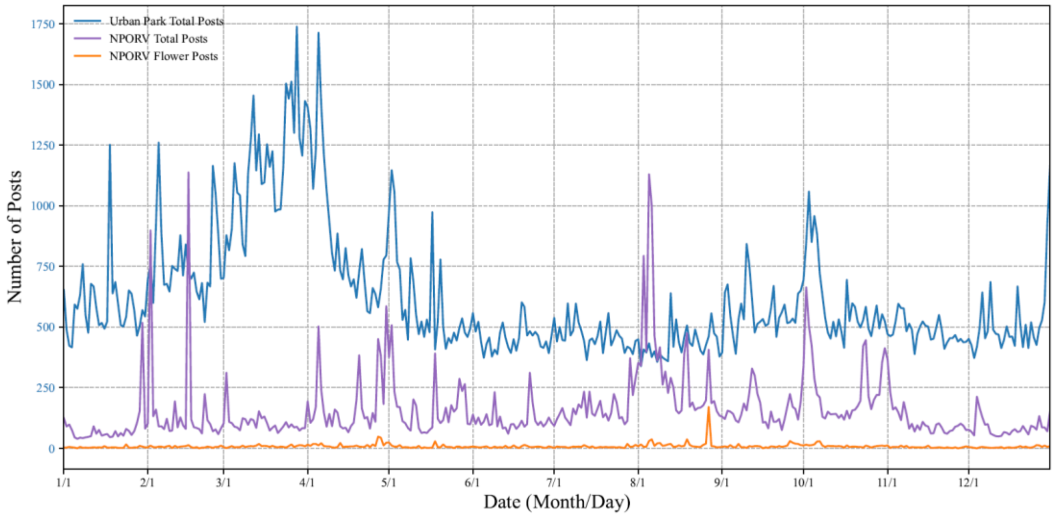

Figure 3. *Daily comparison of urban park, NPORV, and NPORV flower-related Weibo posts*

The blue line corresponds to the total posts about urban parks, showing the daily number of Weibo posts about urban parks. The purple line corresponds to the total posts about NPORV, displaying the daily number of Weibo posts about non-park outdoor recreation venues. The orange line shows the daily number of Weibo posts about flowers in NPORV.

From *Fig. 3*, we can clearly observe the different characteristics of urban parks and NPORV in attracting tourists.

The total number of posts about urban parks shows significant peaks in the spring (March to May) and autumn (September to October). These seasonal peaks may be closely related to the blooming seasons of flowers in the spring and autumn, attracting a large number of tourists to the parks and sharing related content on social media. Despite a decrease in the number of posts in the summer (June to August) and winter (December to February), the activity remains relatively high. This indicates that urban parks have a strong year-round attraction, especially during the flower blooming seasons when tourist enthusiasm is particularly high.

In contrast, the overall trend of total posts about NPORV is relatively stable, with no significant seasonal fluctuations. However, there are noticeable increases at certain points in time, such as during the Spring Festival and Labor Day holidays. These increases are likely due to the higher levels of outdoor activity during holidays, indicating that the attraction of NPORV is more dependent on holidays than natural landscapes.

The number of flower-related posts about NPORV is very low, further indicating that NPORV do not depend on natural landscapes, especially flowers, to attract visitors. This contrasts sharply with urban parks, which experience a significant boost in visitor numbers during the flowering seasons.

From social media data, we can see that urban parks and NPORV are two distinct types of outdoor leisure venues. Urban parks rely on natural landscapes, such as flowers, to attract a large number of tourists during specific seasons, while NPORV primarily depend on special occasions, like holidays, to attract visitors. Therefore, we can infer that the motivations and preferences of tourists when choosing urban parks and NPORV differ significantly.

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Monthly word cloud analysis of park flowers

To better understand how flowers influence visitor numbers and identify seasonal interests among park visitors, we conducted a word cloud analysis of Weibo data. This method visually represents the main flowers and activities related to the park each month, highlighting their seasonal variations.

We aggregated Weibo data on a monthly basis, resulting in twelve text sets. These text sets were segmented into Chinese words to calculate the frequency of each word, generating monthly word clouds and categorizing them by season, as shown in *Fig. 4*. The size of the symbols in the figure indicates the frequency of words, revealing marked seasonal differences.

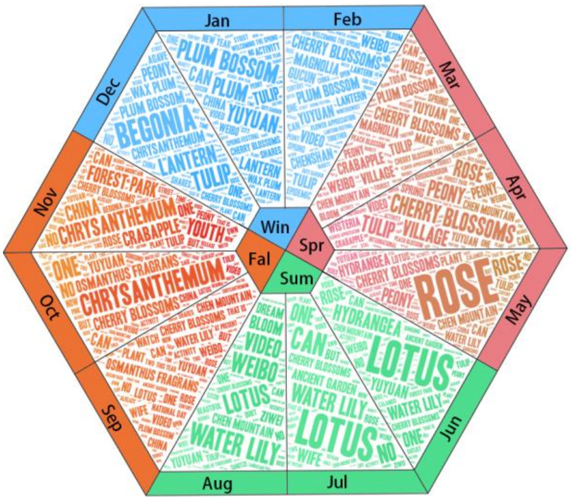

Figure 4. *The monthly variation of word clouds based on Weibo texts*

• Spring (March to May): In spring, the most frequently mentioned words include “cherry blossom", “tulip (Tulipa spp.)" and “peony (Paeonia spp.)". These flowers bloom during this season, drawing numerous visitors. The frequent mentions of cherry blossoms and tulips in March and April reflect their substantial appeal, while May is the peak viewing season for peonies, making spring a high-traffic period for the park.

• Summer (June to August): During summer, keywords such as “lotus" and “water lily (Nymphaea spp.)" appear prominently starting in June and are mentioned frequently throughout the season. These aquatic flowers become major attractions, drawing many visitors for photography and viewing. The viewing activities, especially in July and August, further boost visitor numbers.

• Autumn (September to November): In autumn, keywords like “chrysanthemum (Chrysanthemum spp.) " and “osmanthus (Osmanthus fragrans)" dominate. “Chrysanthemum" is frequently mentioned, with parks hosting chrysanthemum exhibitions and other activities that attract numerous visitors. The fragrance of osmanthus in September and October also draws many visitors, enhancing the park’s appeal.

• Winter (December to February): In winter, keywords include “plum blossom (Prunus mume)" and “lantern festival". Plum blossoms are frequently mentioned in December and January, becoming the main attractions during winter. The park management’s organization of spring flower exhibitions and lantern festivals during the Spring Festival (January to February) also attracts many visitors.

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This word cloud analysis not only identifies seasonal visitor interests but also provides crucial data to support park management and marketing strategies, helping to attract more visitors throughout the year.

Correlation among A_T, A_F and P

By analyzing the pairwise correlations of A_T, A_F, and P across 14 parks, we obtained three sets of correlation values, as shown in *Fig. 5*. The red, green, and blue lines represent the correlations of A_T-A_F, A_F- P, and P-A_T, respectively. Each point on the lines corresponds to a specific park's correlation value. Points closer to the outer edge indicate stronger correlations, while points nearer to the center represent weaker correlations.

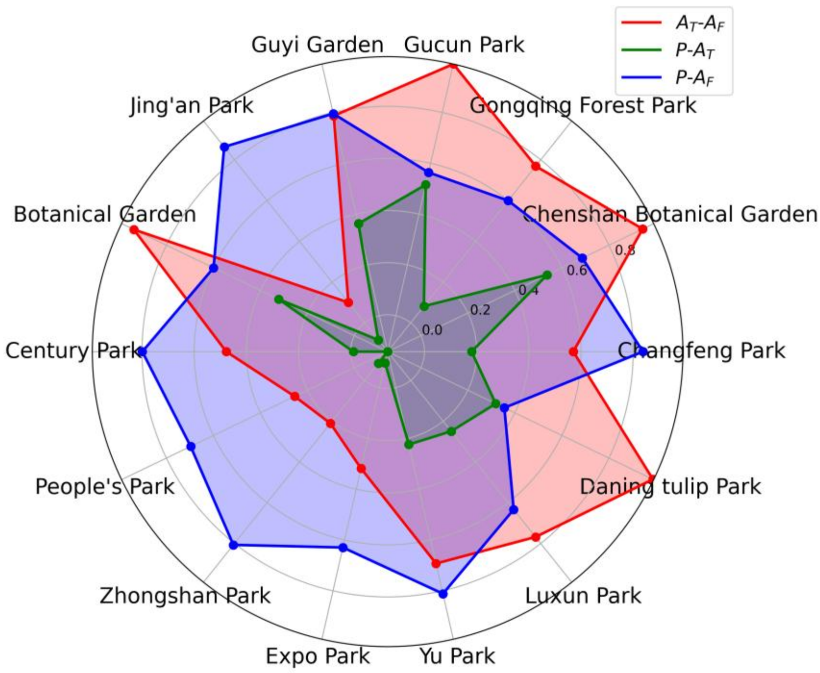

Figure 5. *Correlation among A_T, A_F and P*

The red line shows that most parks have a high A_T-A_F correlation. For instance, Gucun Park, Chenshan Botanical Garden, and Gongqing Forest Park have correlation values close to the outer edge, indicating strong synchronization between total post volume and flower-related discussions in these parks. In contrast, Jing'an Park and Zhongshan Park exhibit lower correlations, with points closer to the center, suggesting that flower-related discussions in these parks are not strongly influenced by changes in total post volume.

The blue line indicates that P-A_F correlations are generally high, with most parks having values above 0.6. Notably, Jing'an Park and People's Park stand out with correlations near the outer edge, reflecting that flower-related topics in these parks receive greater attention during the flowering season.

Comparison results of A_T and A_F

The total number of daily posts can reflect the number of visitors to the park, and the park's attraction to visitors is multifaceted, with flowers being only one part of it. Therefore, A_T does not fully represent the attractiveness of flowers. Only posts related to

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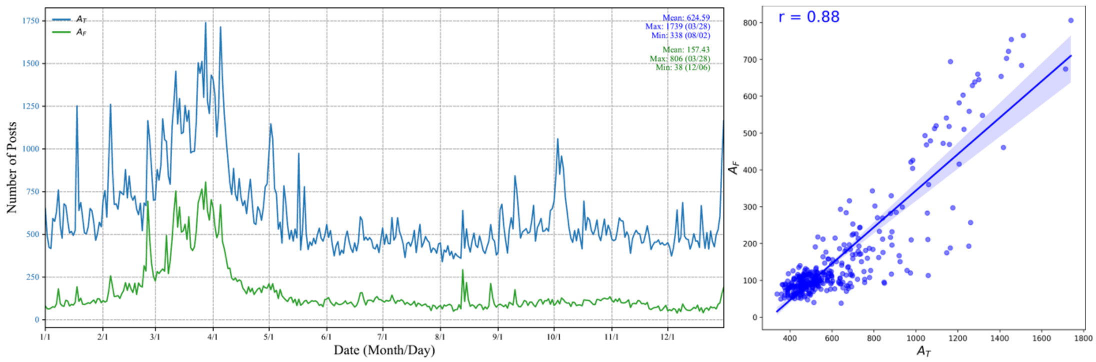
flowers can accurately reflect the appeal of flowers to visitors. Based on this, this subsection performs a statistical analysis of A_T and A_F. *Fig. 6* illustrates the relationship between A_T and A_F through a time series plot (a) and a scatter plot (b).



(a) Time series plot (b) Scatter plot

Figure 6. *Relationship between A_T and A_F*

It can be seen from *Fig. 6(a)* that the overall trends of the two data sets are quite similar, with the total number of posts peaking between March and April, indicating that the park attracted the most visitors during this period. Similarly, the number of flower-related posts reached its highest point at the end of March, indicating that the attractiveness of the park's flowers was strongest at that time. However, A_T shows a significant peak during holidays (e.g., October 1st, National Day), while A_F remains stable, indicating that the attractiveness of flowers is not strongly associated with holidays but is more reflective of seasonality. Overall, the fluctuation in A_F is relatively stable and generally lower than A_T, further confirming that flowers are only part of the park's attraction.

Fig. 6(b) is a scatter plot that illustrates the relationship between A_T and A_F. Each point in the plot represents one day's data, where the horizontal axis shows A_T, and the vertical axis shows A_F. The blue regression line indicates the linear trend between the two variables, with its slope reflecting the influence of total posts on flower-related posts. Most points are distributed near the regression line, indicating a strong positive correlation between total posts and flower-related posts, i.e., as the total number of posts increases, the number of flower-related posts also increases. Correlation analysis shows a Pearson correlation coefficient of r = 0.88, further confirming the strong positive correlation. The points are relatively spread out, particularly in the region with higher total posts, suggesting that on certain days (e.g., during peak flowering periods), an increase in total posts may significantly boost the number of flower-related posts.

Through this data analysis, it is evident that the attractiveness of flowers is mainly affected by seasonal changes rather than holidays. Therefore, when assessing the attractiveness of park flowers to visitors, greater emphasis should be placed on seasonal factors rather than solely relying on the total number of daily posts as a parameter

Comparison results of A_T and P

The previous section explained that A_T does not fully reflect the daily number of visitors, while A_F can more accurately reflect the attraction of flowers to visitors. The

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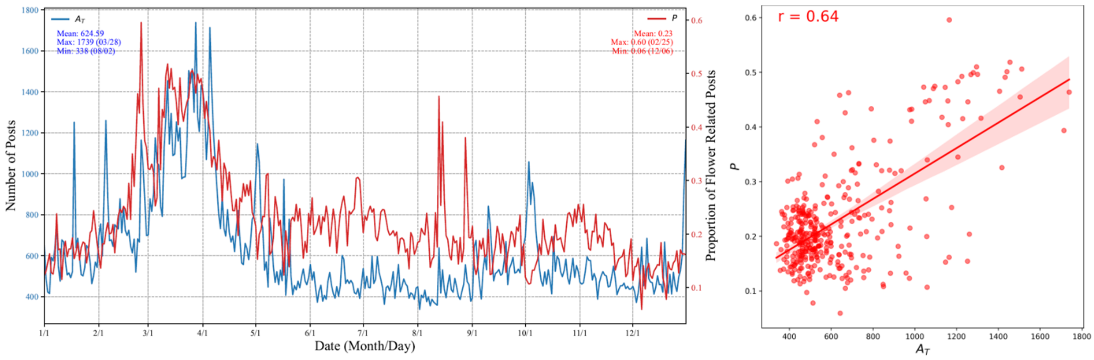
proportion of flower-related posts (P) provides a better reflection of the appeal of flowers to visitors.

Fig. 7 shows how A_T correlates with P through a time series plot (a) and a scatter plot (b). The following points can be observed from the figure.



(a) Time series plot (b) Scatter plot

Figure 7. *Relationship between A_T and P*

• Seasonal fluctuations: On a large time scale, both A_T and P show significant seasonal variations, particularly peaking from March to May. This indicates that in spring and early summer, when flowers are in full bloom, they attract a large number of visitors for viewing and photography, with flowers having the strongest appeal to visitors.

• Impact of holidays: On a smaller time scale, the fluctuations of P often contrast with those of A_T. For instance, during the National Day holiday on October 1st, the A_T value significantly increases while the P value substantially decreases, showing opposite trends. This suggests that during holidays, the number of flower-related posts remains relatively stable since the seasonal appeal of flowers does not intensify due to holidays. However, the total number of posts increases sharply during holidays as more visitors come to the park, leading to a decrease in the proportion of flower-related posts.

• Stability outside blooming seasons: Outside the blooming seasons (e.g., late summer and winter), the fluctuations of P are relatively stable and overall lower than during peak periods. This indicates that during these times, the appeal of flowers to visitors is relatively weak, and other factors might have a greater role in attracting visitors to the park.

• Impact of special events: At certain times, such as in July and September, P shows several noticeable peaks. This may be related to specific flower events or the blooming of flowers in particular areas of the park, suggesting that park management can enhance the appeal of flowers to visitors by organizing flower-related events.

• Long-term trend analysis: The annual data demonstrates the cyclical changes in the appeal of flowers, which can help park managers formulate more targeted marketing and management strategies. For example, focusing on intensive promotion before and after blooming seasons to attract more visitors, while maintaining visitor numbers through other activities during off-seasons.

As can be seen in *Fig. 7(b)*, the Pearson correlation coefficient between A_T and P is 0.64, indicating only a moderate positive correlation. The points are more dispersed compared to the other scatter plots, particularly in the lower regions of A_T and P, suggesting that in most cases, the total number of posts has limited influence on the

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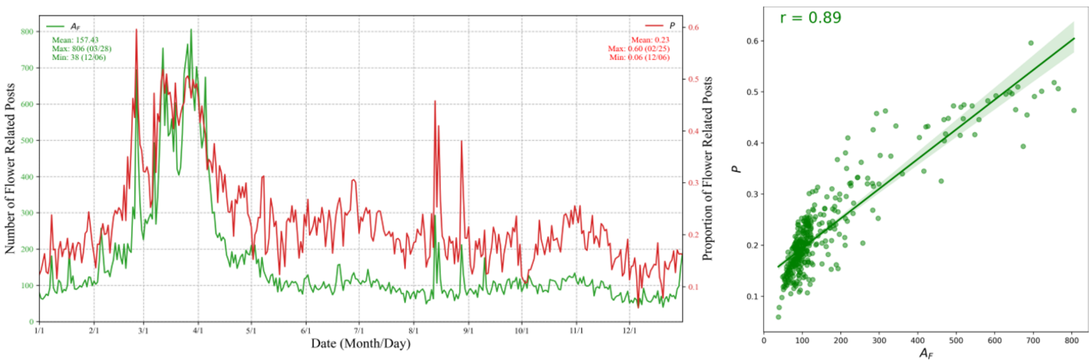
proportion of flower-related posts. A few high P points suggest that on certain days, even when the total number of posts was relatively low, flower-related posts accounted for a large proportion, likely reflecting seasonal discussion peaks or specific events.

This data analysis reveals that the attraction of flowers to visitors is most evident during the blooming seasons and less significant during holidays. Therefore, the appeal of flowers is primarily influenced by seasonal changes rather than holidays. Specifically, spring and early summer are the periods when flowers have the strongest appeal, while during other times, although the overall number of visitors to the park may increase, the attraction of flowers to visitors does not change significantly. This indicates that when formulating park management and promotion strategies, more attention should be paid to the blooming periods, fully utilizing the flower resources during these times to attract visitors, while during holidays, other factors should be considered to attract visitors.

Comparison results of A_F and P

Fig. 8 demonstrates the connection between A_F and P by combining a time series plot (a) and a scatter plot (b).



(a) Time series plot (b) Scatter plot

Figure 8. *Relationship between A_F and P*

The trends of A_F and P in *Fig. 8(a)* are closely related. Both show peaks during the flowering season, especially from March to April, suggesting that flowers attract more attention during this period. The highest P value occurs when flower-related discussions dominate the overall posts.

Compared to A_F, P fluctuates more sharply, especially in the off-season. This shows that even a small change in flower-related posts can significantly affect the proportion. On the other hand, A_F stays relatively stable throughout the year, with occasional peaks during flower events.

As can be seen in *Fig. 8(b)*, the Pearson correlation coefficient between A_F and P is 0.89, demonstrating a very strong positive correlation between flower-related posts and their proportion. Most points are densely distributed near the green regression line, indicating that the variation in flower-related posts is closely aligned with the variation in their proportion. A few high A_F points suggest that during certain periods, flower-related discussions dominated, likely due to flowering seasons or specific floral events.

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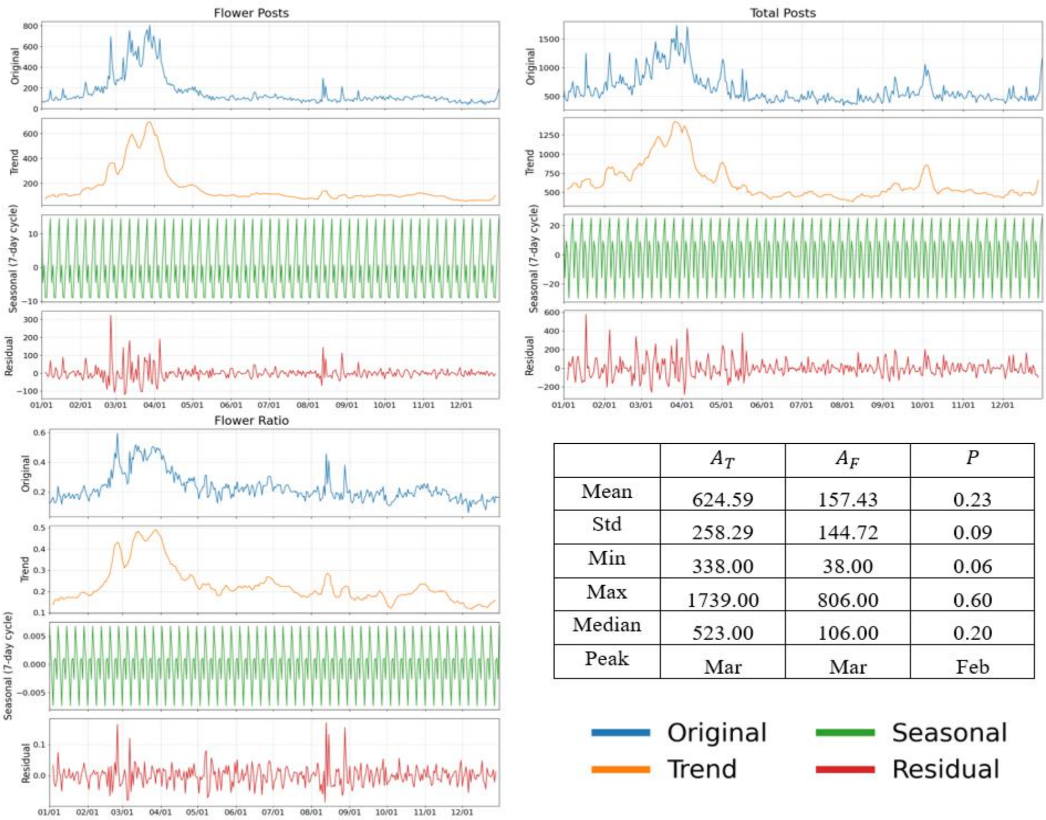
Time series decomposition

The time series decomposition results are shown in *Fig. 9*. From the overall trend, the values of A_T, A_F, and P gradually increase at the beginning of the year, reaching their peak in March and April, before declining afterward. This indicates that during the spring flowering season, people's posting activity, interest in flowers, and the proportion of flower-related discussions all rise significantly. This trend aligns closely with the seasonal effect of spring flower blooming, further confirming the heightened public attention to flower-related topics in spring.



	A_T	A_F	P
Mean	624.59	157.43	0.23
Std	258.29	144.72	0.09
Min	338.00	38.00	0.06
Max	1739.00	806.00	0.60
Median	523.00	106.00	0.20
Peak	Mar	Mar	Feb

Figure 9. *Time series decomposition of flower-related social media data*

From a cyclic perspective, all variables exhibit a clear 7-day periodic fluctuation, likely influenced by the weekly activity rhythm of social media (e.g., increased engagement on weekends). Additionally, the residual component shows significant fluctuations during March and April, suggesting the presence of abnormal variations beyond the trend and seasonality. These anomalies may be related to springtime flower-related events, social media trends, or sudden bursts of discussion.

Classification of park types based on A_T and A_F fluctuations

In order to better study the relationship between the number of visitors and flowers, I conducted an independent analysis of data from various parks. *Fig. S1~ Fig. S15* shows the statistics of A_T and A_F for seven selected parks. Based on the characteristics presented by the user data, parks can be classified into the following three categories: single-peak parks, double-peak parks, and multi-peak parks.

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When the data volume for a park is small, it may lack statistical significance. In such cases, even minor changes in A_F and A_T can lead to substantial fluctuations in P.

Gucun Park fits the characteristics of a single-peak park. During the period from March to May, the number of visitors shows a distinct peak, with an A_T value reaching 600. This corresponds with the cherry blossom season in the park, making this period the most spectacular time in Gucun Park.

Chenshan Botanical Gardens boasts a wide variety of plants, blooming throughout the year. Its annual visitor count and P exhibit a noticeable peak in the spring. During other periods, similar to Gucun Park, there are no significant peaks. Although the peak visitor count during the flowering season is lower than that of Gucun Park, the number of visitors during non-flowering periods is higher due to the richer variety of plant species in the botanical garden, making it more attractive to visitors.

Gongqing Forest Park exhibits a clear double-peak characteristic in visitor numbers, with peaks in both spring and autumn. The A_F peak in autumn is particularly notable, associated with the annual chrysanthemum exhibition, demonstrating the attraction of flowers to park visitors. Shanghai Botanical Gardens also shows a similar double-peak characteristic, although the autumn peak is lower than the spring peak.

Guyi Gardens, a famous classical garden with a rich variety of flowers, exhibits multiple peaks in visitor numbers throughout the spring, summer, autumn, and winter, indicating periodic fluctuations. The cherry blossoms and peonies in spring, lotuses and water lilies in summer, maples **(**Acer spp.**)** and osmanthus in autumn, and plum blossoms in winter make it a premier place for flower viewing. Shanghai Century Park, as the largest free park in Shanghai, also shows a similar multi-peak characteristic.

Shanghai People's Park falls into the category of parks with low data volume. Due to the sparse data, even small changes in A_T and A_F can cause significant fluctuations in P. Therefore, P has statistical significance only when the data volume is large enough to truly reflect the attraction of flowers to visitors.

Sankey diagram: Relationship between parks and their flowers

To better analyze the relationship between various parks and their flowers, we employed a Sankey diagram to present the data. Sankey diagrams are effective tools for visualizing complex flows and proportions, allowing us to identify patterns and trends in park visitation and flower-related mentions (Yang et al., 2024). We used cleaned data to identify high-frequency words, build a word frequency matrix, and ultimately draw the Sankey diagram, as shown in *Fig. 10*. This diagram illustrates the strength of associations between different parks and flowers, with nodes representing parks and flowers, and the width of the connecting lines indicating the number of mentions for each flower in each park.

From the diagram, it is clear that Gucun Park has the strongest association with cherry blossoms, making them the most frequently mentioned flowers in the park. This indicates that Gucun Park attracts a large number of visitors during the cherry blossom season. Similarly, Chenshan Botanical Garden has a high number of mentions for roses roses **(**Rosa spp.), highlighting its significant appeal to visitors. This makes sense given the popularity of Rose Island, a major feature of the garden. Shanghai Botanical Garden has mentions of various flowers, including roses and tulips, which means it attracts visitors year-round by showcasing different flowers in each season. In contrast, Changfeng Park and Jing'an Park have fewer mentions, which could mean there's less data. These parks might consider adding more flower varieties or improving their displays to attract more visitors.

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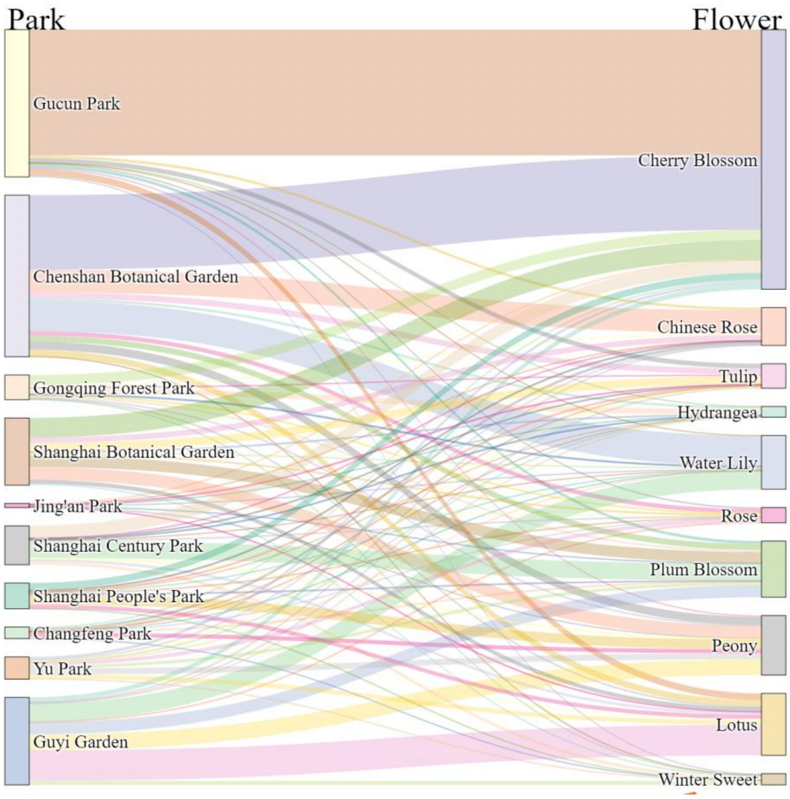

Figure 10. *Relationships between parks and flowers in Sankey diagram*

The data shows clear seasonal trends, such as the high mentions of cherry blossoms in Gucun Park during cherry blossom season. The blooming periods of seasonal flowers have a strong influence on visitor numbers and engagement. Parks with a wide range of popular flowers, such as Shanghai Botanical Garden, can maintain high visitor interest throughout the year. This variety helps draw visitors year-round and mitigates the effects of off-seasons. In contrast, parks with less data, like Changfeng Park, show significant fluctuations in the interaction ratio P, which may not hold statistical significance.

Using this method, park managers can better understand visitor preferences and make informed decisions on park planning and resource allocation. This approach will boost the park's attractiveness and competitiveness. Data-driven decisions will help parks stay ahead in future development.

Discussion

Urban parks possess a multitude of attractions, with flowers being a prominent highlight that significantly enhances visitor footfall. Consequently, scientifically evaluating the influence of floral elements on visitor attraction is crucial for effective park management and strategic optimization (Ye et al., 2022). Given that social media data accurately reflects user interests and preferences, this study leverages this resource to develop an analytical model that thoroughly examines the role of flower-related data in enhancing urban park appeal. Incorporating comprehensive processes such as data collection, cleaning, extraction, and analysis, this model not only assesses the attractiveness of flowers to visitors but also analyzes the characteristics and impacts of

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various park types and their key floral varieties, providing a scientific foundation for the parks' ongoing development and management.

Good location + free entry ≠ high social media data volume

During the data collection phase, we selected parks with substantial data volumes to facilitate subsequent processing and analysis. However, the study found that a prime geographical location and extensive park areas do not necessarily translate into higher volumes of social media data (Yang et al., 2022). For instance, Shanghai People's Park, centrally located with an expansive area of 98,200 square meters and free entry, is a popular historic park, yet its social media data volume is surpassed by Yu Garden. Despite being only a quarter of its size and charging entry fees of 30 RMB in the off-season and 40 RMB during peak season, Yu Garden boasts eight times the average annual Weibo data volume compared of People's Park.

These differences likely result from a combination of factors. As a quintessential representation of classical Chinese gardens, Yu Garden not only possesses rich historical and cultural significance and a unique architectural style but also continually attracts visitors with its flowers blooming throughout the year, particularly appealing to tourists from other regions (Kingsley et al., 2022). In contrast, while Shanghai People's Park serves some recreational purposes, its somewhat outdated facilities and limited variety of plants are less appealing to non-local tourists, and its primary visitors are local residents who are generally older and less frequent or proficient users of social media (Daniels and Powers, 2024). Thus, despite both parks being situated in densely populated urban centers, Yu Garden's content is more conducive to social media sharing, resulting in greater social media data output.

How do A_T, A_F and P reflect the attraction of parks to visitors?

From the cleaned social media data, we can derive A_T, A_F, and P to reflect the allure of city parks to visitors from various perspectives. The A_T of a single park reflects the combined effects of park features, visitor numbers, and visitor demographics, thereby demonstrating the overall appeal of the park to visitors. While many factors attract visitors, flowers are just one component, and A_F represents the size of the visitor demographic interested in flowers (Wan et al., 2021).

Due to significant differences in the size and design of various parks, directly comparing A_T and A_F across parks is not meaningful. Instead, P clearly demonstrates the proportion of visitors attracted to parks by flowers. This metric is particularly important for analyzing the impact of flowers on attracting visitors to urban parks.

Characteristics of P

P=A_F/A_T, this proportion is influenced by both A_F and A_T. Visitors are more likely to post about flowers on social media during the flowering season, hence A_F reflects the volume of data related to flowers, and its variation indicates an association with the flowering season. Fluctuations in A_F that are not synchronized with the flowering season, may cause fluctuations in P.

On a larger time scale, A_F is influenced by the flowering season, showing fluctuations similar to those of the flowering season; on a smaller time scale, A_F exhibits periodic fluctuations**,** such as higher data volumes on weekends and holidays compared to weekdays, demonstrating significant periodic fluctuations. Conversely, A_T, while also

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influenced by the flowering season on a large time scale, is more susceptible to various hot events on a smaller time scale, leading to more dramatic fluctuations.

P exhibits two distinct trends on different time scales: (1) On a larger time scale, P generally follows the trends of A_T and A_F. During non-flowering periods, when interest in flowers wanes and the proportion of related topics decreases, P is lower, indicating that flowers have a weaker attraction to park visitors. During the flowering season, as people's frequency of outings increases, along with social media posting activity, and flowers become a hot topic, both A_T and A_F grow, leading to an upward trend in P. This indicates that during the flowering season, visitors' attention to flowers increases, enhancing the flowers' appeal. (2) On a smaller time scale, P may show trends opposite to A_T. When A_F remains relatively stable, an increase in A_T can lead to a decrease in P. For instance, when a park experiences a hot event unrelated to flowers, A_T may spike sharply, while the impact on A_F is minimal, causing a short-term decrease in P; once the hot event passes, A_T falls, and P correspondently increases, showing a trend opposite to that of A_T.

Therefore, on a smaller time scale, R's fluctuations may be pronounced, and its changes may not accurately reflect the attraction of flowers to park visitors. In contrast, fluctuations of P observed on a larger time scale truly reflect the attraction of flowers to park visitors, making this analysis meaningful.

Flower varieties in urban parks: Star flowers vs. floral diversity

The Sankey diagram in *Fig. 10* reveals that deciding whether to focus on star flowers or promote floral diversity is a crucial management decision for urban parks (Shoaib et al., 2021).

For public parks, concentrating resources on creating one or two-star flower brands is more beneficial than evenly investing in multiple flower varieties. The advantages of focusing on star flowers include creating a strong brand effect, as star flowers can become iconic features of the park (Patel et al., 2020). For example, the cherry blossoms at Gucun Park and the roses at Chenshan Botanical Garden are major attractions. By focusing resources on a few types of flowers, parks can provide better maintenance and displays, improving the visitor experience (Bayón et al., 2021). These star flowers are also easier to promote, making the park more recognizable and appealing (Zaninotto et al., 2023). Events like cherry blossom festivals or rose exhibitions can attract specific groups of visitors.

Promoting floral diversity also has unique benefits. A variety of flowers ensures that the park remains attractive throughout the year, reducing the impact of off-seasons (Ibrahim et al., 2020). For example, the Shanghai Botanical Garden attracts many visitors year-round by showcasing different flowers in each season. Additionally, having a diverse range of plants helps maintain the park's ecological balance, promotes biodiversity, and improve environmental quality (Nguyen et al., 2023). Different flowers appeal to various interests, providing a rich and diverse experience for all visitors.

In practice, parks can combine both strategies, adjusting according to their characteristics and visitor needs. For flowers with clear seasonal advantages, such as cherry blossoms and plum blossoms, parks can focus on promoting them as star flowers. In other seasons, displaying a wider variety of flowers can help maintain steady interest. By following this integrated approach, park managers can allocate resources more effectively, boost the park's overall appeal and competitiveness, and meet the diverse needs of visitors.

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Limitations and future research

There are some limitations in this study. It relies solely on text data from Sina Weibo, which is a limited source and format. Social media data are inherently biased toward positivity (Koenig-Lewis et al., 2021). This positivity bias may distort the analysis. Furthermore, the demographic characteristics of Sina Weibo users, such as age, gender, and educational level, might not align with the broader population (Zheng et al., 2021). The data are insufficient for groups that are less active on social media, such as children and the elderly (Donahue et al., 2018).

To address these shortcomings, future research could benefit from employing both online and offline methodologies, integrating data across various social media platforms. Additionally, leveraging image data from social media, analyzed through computer vision techniques (Huai et al., 2022), could provide a more nuanced understanding of visitor behaviors (Wan et al., 2021). This approach would not only broaden the data spectrum but also enhance the representativeness and accuracy of the findings, offering a more holistic view of the research subject.

Conclusion

In this paper, we developed a social media data analysis model to quantify the attractiveness of flowers to visitors in urban parks. The results indicate significant differences in the attractions between parks and NPORV, and demonstrate seasonal variations in visitor numbers to parks. It was found that although A_T and A_F are related to visitor numbers and interest in flowers, they do not directly represent the attractiveness of flowers. P effectively reflects the allure of flowers to visitors. Fluctuations in P should be analyzed over both large and small time scales. On a larger scale, these fluctuations exhibit seasonal patterns that reflect the seasonal appeal of flowers, whereas on a smaller scale, the variations in P might show trends opposite to those of A_T. By using NPL, we discovered that certain predominant flower types are more effective in attracting visitors. Thus, park managers should balance the selection of key flower species and diversity to enhance visitor attraction more effectively.

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Conflict of Interest. The authors declare no conflict of interest.

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APPENDIX

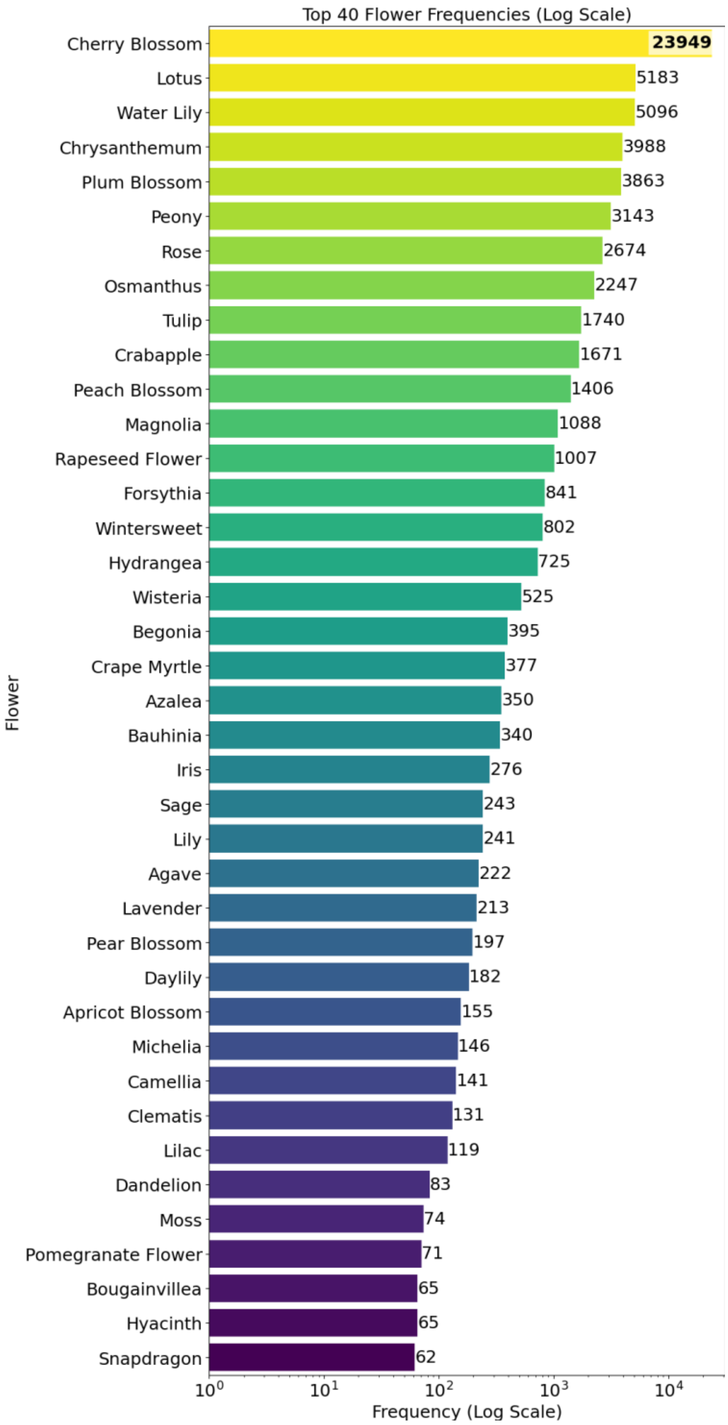

Figure S1. *Top 40 most frequently mentioned flowers*

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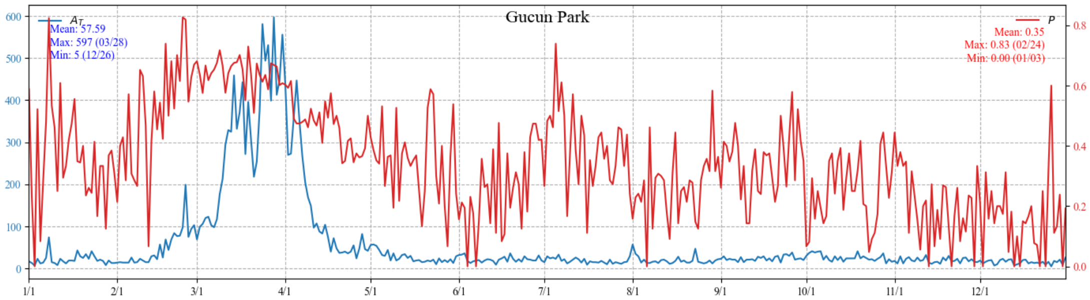

Figure S2. *A_T and P of Gucun Park*

Figure S3. *A_F and A_T of Gucun Park*

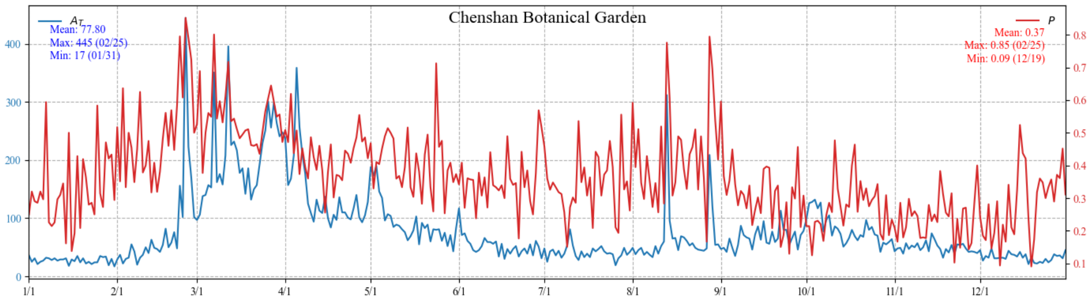

Figure S4. *A_T and P of Chenshan Botanical Garden*

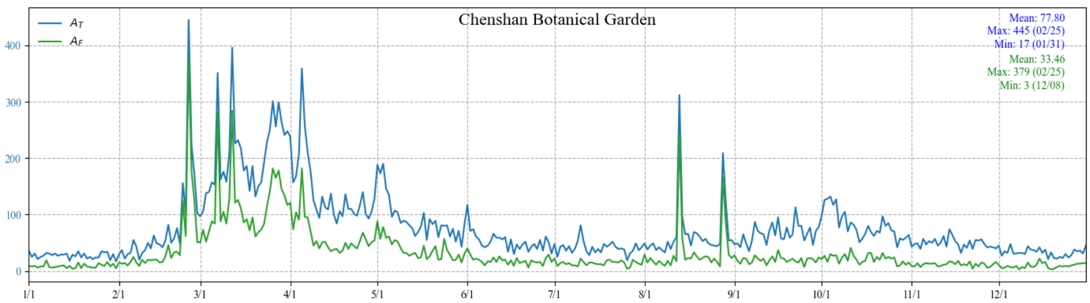

Figure S5. *A_F and A_T of Chenshan Botanical Garden*

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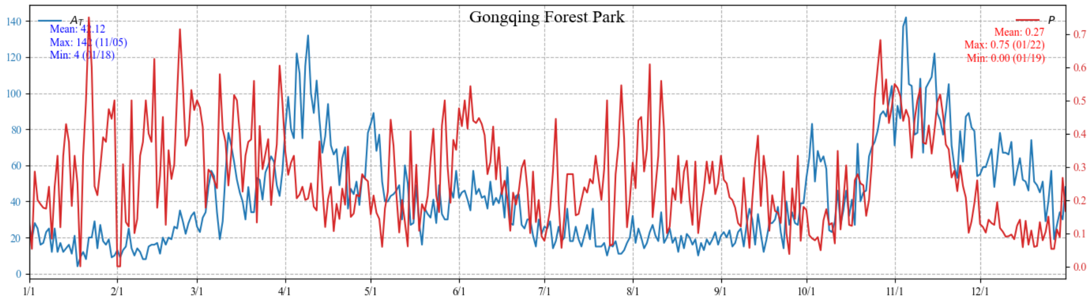

Figure S6. *A_T and P of Gongqing Forest Park*

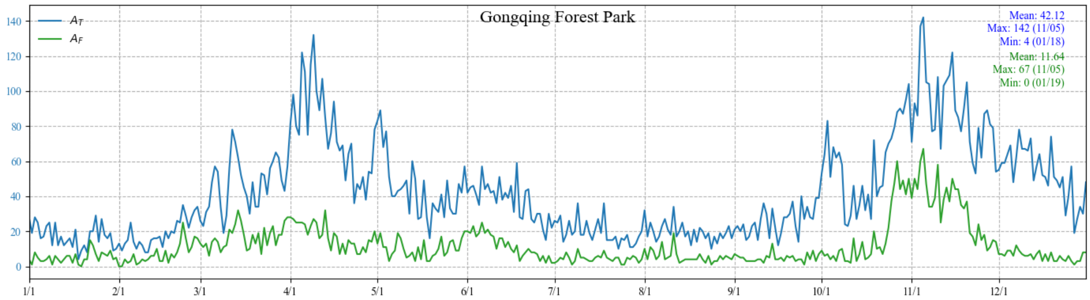

Figure S7. *A_F and A_T of Gongqing Forest Park*

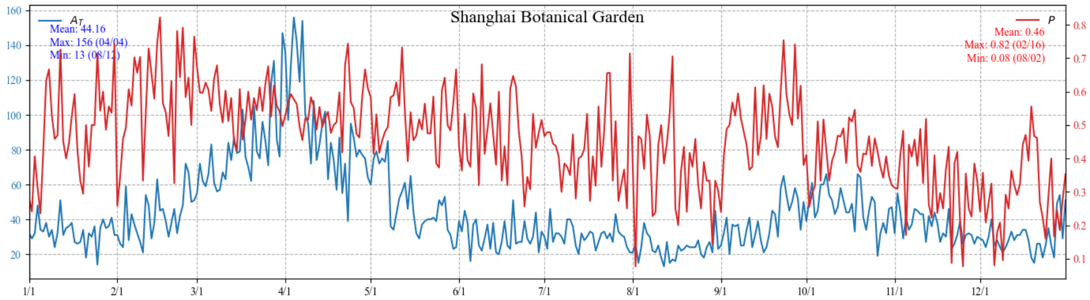

Figure S8. *A_T and P of Shanghai Botanical Garden*

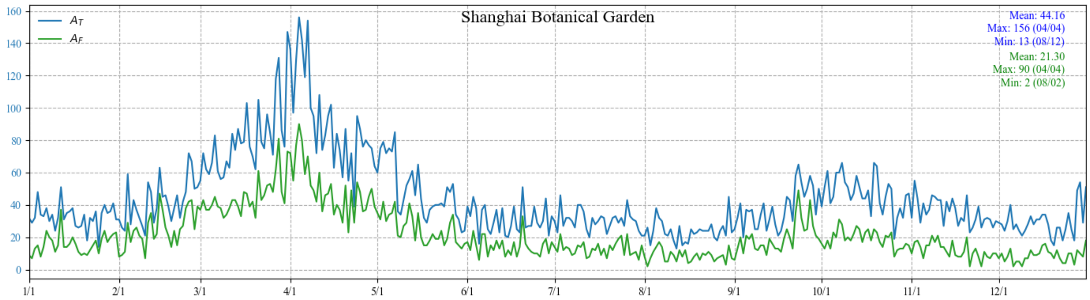

Figure S9. *A_F and A_T of Shanghai Botanical Garden*

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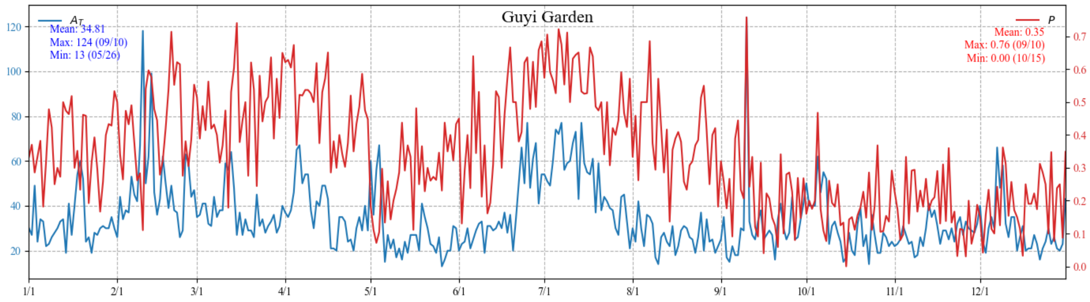

Figure S10. *A_T and P of Guyi Garden*

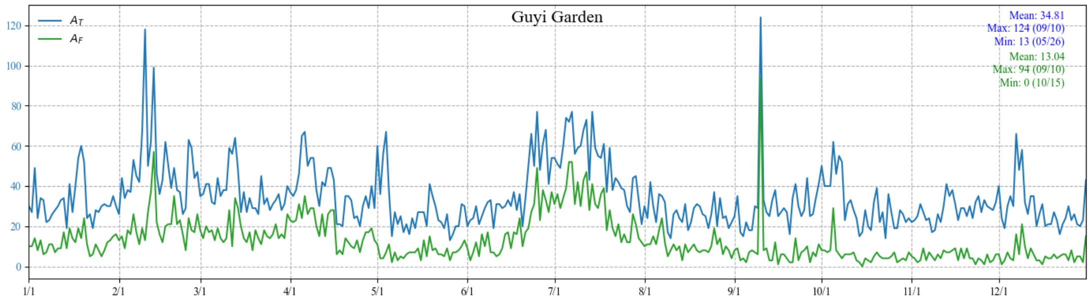

Figure S11. *A_F and A_T of Guyi Garden*

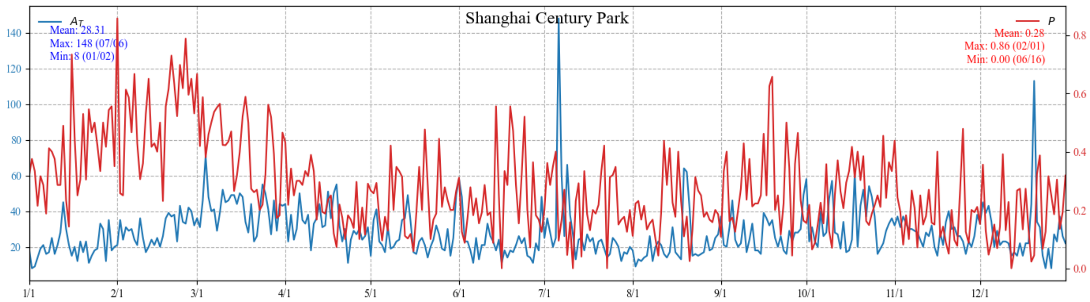

Figure S12. *A_T and P of Shanghai Century Park*

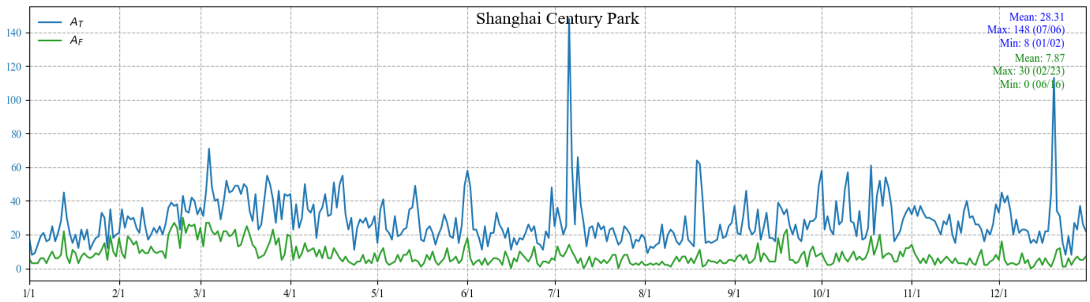

Figure S13. *A_F and A_T of Shanghai Century Park*

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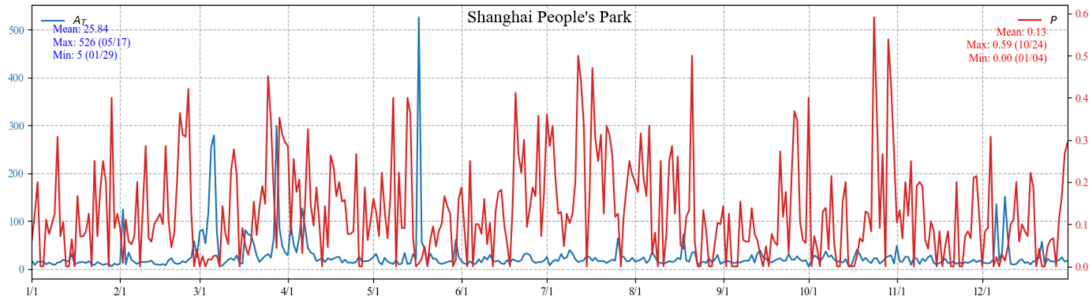

Figure S14. *A_T and P of Shanghai People's Park*

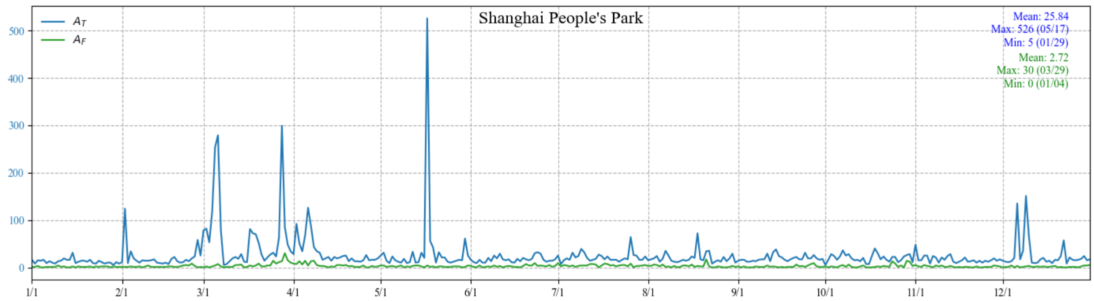

Figure S15. *A_F and A_T of Shanghai People's Park*

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