ASSESSMENT OF FLORAL ATTRACTIVENESS USING INTEGRATED INDICATORS: SEASONAL TREND ANALYSIS AND PREDICTIVE MODELING IN URBAN PARKS OF CHINA

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(Received 13th Jul 2025; accepted 23rd Dec 2025)

Abstract. The attractiveness of floral landscapes in urban parks plays a significant role in enhancing visitor experience and optimizing spatial management. However, traditional methods for evaluating attractiveness often rely on a single dimension, making it difficult to comprehensively capture the dynamic changes in visitor attention. This study proposes a Floral Attractiveness Index (FAI) based on social media data from platforms such as Weibo and Ctrip, integrating the proportion of flower-related content and posting activity to characterize public attention trends toward floral landscapes in urban parks. Through the analysis of data from ten representative parks in Shanghai, China, the results show that the FAI reliably reflects temporal variations in floral attractiveness and demonstrates strong fitting and predictive performance. Most parks exhibit a bimodal trend, with peaks in spring and autumn, which is consistent with the seasonal flowering patterns of ornamental plants in Shanghai. The dominant factors influencing attractiveness vary significantly across different parks. Based on the above analysis, this study further proposes specific optimization recommendations for flowering schedule planning, event organization, and visitor management. This research provides a new quantitative approach for understanding public perception mechanisms in urban ecological spaces and offers data support for smart cultural and tourism management.
Keywords: *flowering phenology, urban green spaces, social media data, temporal dynamics, machine learning*

Introduction

Urban parks are important leisure places for urban residents. They are not only key components of urban natural landscapes, but also crucial regulators of the urban ecosystem (Li et al., 2024), providing residents with a peaceful space away from the hustle and bustle of the city for social activities, physical exercise and spiritual relaxation (Cao et al., 2024). Seasonal flowers, such as cherry blossoms in spring and lotus flowers in summer, attract many visitors. This contributes significantly to the park's seasonal appeal (Giedych and Maksymiuk, 2017; Tabrizi et al., 2023). Therefore, exploring the relationship between flowers and park attraction is important. It is also crucial to plan flower-themed activities to enhance park appeal.

Studies have shown that park attractiveness is influenced by many factors, such as geographical location (Moran et al., 2020), design layout (Jeon and Hong, 2015), biodiversity (Gonçalves et al., 2021), landscape planning (Zhu et al., 2021), leisure facilities, transportation accessibility and safety (Han et al., 2018). In addition, the quality of the surroundings of the park and its cultural and historical context also have a significant impact on its attraction (Nasution et al., 2021). Flowers, as an important part of the park landscape and biodiversity, are a key factor in attracting visitors. The rich

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_12791299

variety of flowers and their related activities not only directly affect the number of visitors and length of stay, but also enhance the social and cultural appeal of the park through seasonal exhibitions and festivals such as the cherry blossom festival and the chrysanthemum show. These activities not only provide visual enjoyment for visitors, but also further enhance the overall appeal of the park by enhancing social interaction and cultural experiences.

It is still unclear how to measure the impact of flowers on park appeal. Traditional research mainly uses questionnaires, interviews (Cattano et al., 2023) and observations of user behavior (Yang and Li, 2025). These methods help understand tourists' needs and preferences. However, they are time-consuming and require a lot of manpower. They also have limited sample sizes. Results can be affected by observer bias and social expectations (Wang et al., 2024). Traditional analysis methods are difficult to deal with heterogeneous data (such as text, images and videos) effectively, which limits the exploration of tourist behavior patterns and future trends (Chang et al., 2024; Khan et al., 2024).

With the rise of big data and social media, researchers have gained new perspectives to analyze visitor behavior and the attractiveness of park flowers. On social media platforms, users spontaneously share their experiences, feelings and activities in the park, generating a wealth of real and valuable data (Niu and Silva, 2020; Volenec et al., 2021; Wan et al., 2021). Using a web crawler, researchers can collect data, clean and analyze it with natural language processing (NLP) technology, and extract information about tourist behavior, emotions, and preferences. This social media-based research approach not only improves the efficiency of data collection, but also enables more detailed analysis of tourists' emotions and attention to flowers.

Existing studies have attempted to use flower-related posts on social media to measure the attractiveness of urban parks. For example, Mou et al. (2023) analyzed the number of posts to assess the attractiveness of specific flowers to visitors, thereby revealing the relationship between visitor flow and social media activity. Zheng proposed using the proportion of flower-related content in total posts as an interest indicator to explore the temporal and spatial variations in floral attractiveness (Zheng and Huang, 2025). However, existing methods still face certain limitations in empirical applications: (1) Relying solely on the proportion of flower-related posts may fail to accurately reflect actual attention intensity when there are large fluctuations in visitor activity. (2) Attractiveness analyses are mostly based on daily-scale raw data, lacking extraction and representation of trend structures, which limits their potential for cross-period comparison and trend forecasting.

This study proposes a new model for floral attractiveness. We constructed a weighted attractiveness indicator that integrates total post volume and the proportion of flower-related content, aiming to capture both the intensity and breadth of public attention. For temporal modeling, a sliding window mechanism is introduced to identify attractiveness trends, and parks are clustered based on their trend characteristics. To enhance practical value, we further developed a predictive model to conduct short-term forecasting of future changes in floral attractiveness.

Study area and data

This study selected ten representative parks in Shanghai, China, as the research subjects. These parks include Changfeng Park, Chenshan Botanical Garden, Gongqing

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN1785 0037 (Online)
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Forest Park, Gucun Park, Guyi Garden, Jing'an Park, Shanghai Botanical Garden, Century Park, People's Park, and Yu Garden, covering nine administrative districts across the city. The study area is shown in *Figure 1*. Park types are diverse, including botanical gardens and forest parks, as well as comprehensive parks and historic gardens located in central urban areas. Planting schemes generally consist of trees, shrubs, and herbaceous groundcover, and commonly include lawns, flower borders or flower beds, as well as aquatic plants. Floral landscapes are mainly composed of ornamental flowering trees, flowering shrubs, and seasonal flowers, while parks differ in their flowering schedules and the scale of floral arrangements.

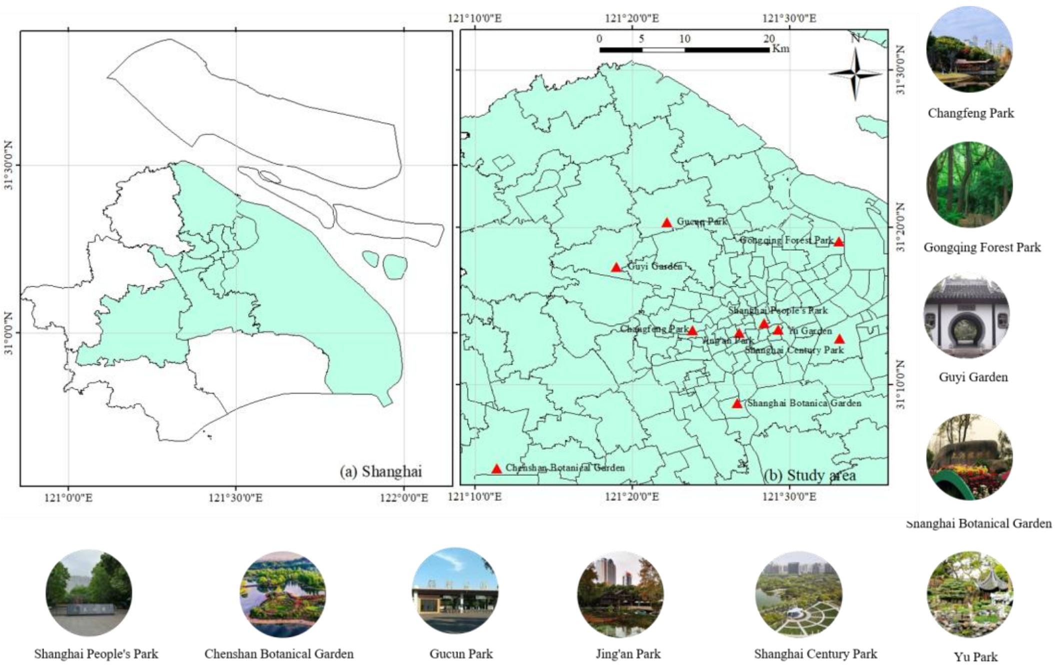

Figure 1. *Study area*

The data for this study were obtained from two Chinese social media platforms: Weibo and Ctrip. Weibo provides user-generated posts that reflect the public's real-time perceptions of parks and floral content. Ctrip provides structured visitor review data, including ratings and subjective feedback. The data were collected using a Python-based web crawler, which simulated browser behavior to parse HTML pages and extract fields such as user ID, location, review time, and review text.

In addition to the textual content used to construct FAI, this study also extracted location-based check-in records corresponding to the ten parks from Weibo data. We filtered location names by exact matches to the Chinese and English names of each park, counted daily check-ins for each park from 2014 to 2023, and aligned them with posting data from the same period. The check-in data are used only to support the validation of FAI temporal patterns by comparing peak periods with posting data. They are not involved in index construction and are not used as inputs to the prediction model.

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Method

This study consists of five main steps: data preprocessing, indicator construction, trend smoothing, correlation analysis, and trend forecasting. The technical framework is illustrated in *Figure 2*.

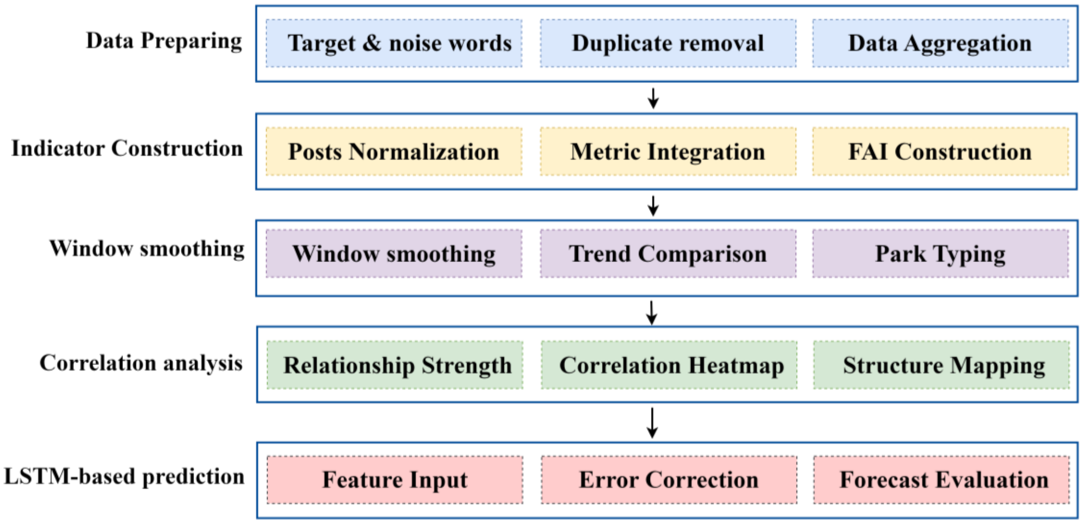

Figure 2. *Technical framework*

Data preprocessing

After data collection, cleaning is required to ensure the accuracy and validity of the data. The data cleaning process includes the following steps:

(1) Inspect and handle records missing key fields. For records missing timestamps, a time inference method based on adjacent data is applied to reasonably complete the information, ensuring data integrity (Zhang et al., 2021; Qiu et al., 2022).

(2) Identify and remove duplicate Weibo posts. By comparing fields such as User ID, Time, and Text, duplicate records are identified and removed to prevent data redundancy from biasing the analysis results (Groen et al., 2020; Mullaly et al., 2023).

(3) Filter out content unrelated to the study (Arru et al., 2021). Preliminary analysis revealed a large amount of irrelevant data, such as posts containing rental information. Therefore, these noisy data were removed from the sample.

After completing the initial cleaning, we obtained social media data for each park. To further extract flower-related content, this study introduced target words and noise words (Niu and Silva, 2020; Timilsina et al., 2020). Target words refer to terms that accurately represent flowers and plants. In this study, we selected 120 common flower names as target words to extract data related to floral content in parks. Noise words refer to terms that contain flower-related characters but do not actually refer to plants. For example, the word “花生”, which contains the character “花” (flower), actually refers to the nut “peanut” rather than a flower in the botanical sense.

We selected 60 common noise words to filter out irrelevant data. Some of the target words and noise words used in this study are shown in *Table 1*.

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***Table 1.** Most common target words and noise words for flowers*

Category	Word List
Target words	花 (flower)、丁香 (lilac)、桂花 (osmanthus)、海棠 (crabapple)、荷花 (lotus)、菊花 (chrysanthemum)、腊梅 (wintersweet)、梨花 (pear blossom)、梅花 (plum blossom)、牡丹 (peony)、芍药 (herbaceous peony)、桃花 (peach blossom)、杏花 (apricot blossom)、樱花 (cherry blossom)、迎春 (winter jasmine)、玉兰 (magnolia)、郁金香 (tulip)、月季 (rose)、紫薇 (crape myrtle)、睡莲 (water lily)、栀子花 (gardenia)、木兰 (magnolia)、山茶花 (camellia)、杜鹃花 (rhododendron)、茉莉花 (jasmine)、百合 (lily)、玫瑰 (rose)、含笑 (michelia)、合欢花 (silk tree)、风信子 (hyacinth)
Noise words	窗花 (window flower)、葱花 (green onion flower)、雕花 (carving)、豆腐花 (tofu pudding)、风花雪月 (romantic affairs)、桂花糖 (osmanthus sugar)、花茶 (flower tea)、花痴 (infatuation)、花店 (flower shop)、花费 (expense)、花糕 (flower cake)、花好月圆 (happy ending)、花蝴蝶 (butterfly)、花花世界 (colorful world)、花卷 (flower roll)、花魁 (courtesan)、花露水 (floral water)、花猫 (spotted cat)、花盆鞋 (flowerpot shoes)、花瓶 (vase)、花生 (peanut)、花纹 (pattern)、花絮 (highlights)、花样 (pattern)、火花 (spark)、葵花子 (sunflower seed)、浪花 (wave)、泪花 (tear)、柳暗花明 (light at the end of the tunnel)、梅花鹿 (sika deer)

Construction of floral attractiveness index

To accurately measure visitors' attention to floral landscapes in parks, this section constructs the Floral Attractiveness Index (FAI) as a metric for the daily intensity of floral attractiveness. The index integrates the relative proportion of flower-related content on social media and the overall level of visitor activity to enhance its representativeness and stability.

Let $flower\_posts_d$ be the number of texts containing flower-related keywords on day d, and $total\_posts_d$ be the total number of texts on that day. Then, the proportion of flower-related attention is calculated as:

$$flower\_ratio_d = \frac{flower\_posts_d}{total\_posts_d} \quad \text{(Eq.1)}$$

This ratio is used to measure the level of attention given to flowers in users' daily posts. However, on days with low total post volume, this indicator is susceptible to outliers and lacks stability. To enhance the consistency of data scale and the ability for cross-temporal and spatial comparison, a normalized posting volume indicator is introduced, defined as follows:

$$normalized\_total\_posts_d = \frac{total\_posts_d}{max(total\_posts)} \quad \text{(Eq.2)}$$

Here, the denominator represents the maximum daily post count for the park throughout the year. This normalized indicator reflects the relative level of visitor activity within the annual cycle and helps eliminate differences in posting baselines among parks. Based on the two variables above, the FAI is expressed as follows:

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$$FAI_d = 0.5 \times flower\_ratio_d + 0.5 \times normalized\_total\_posts_d \qquad \text{(Eq.3)}$$

By integrating the proportion of flower-related content and visitor activity with equal weighting, the FAI captures both visitor attention and spatial popularity. This indicator exhibits lower fluctuation over time and, compared to traditional ratio-based methods, is more suitable for systematic modeling and analysis of urban park attractiveness across different time periods and parks.

Sliding trend analysis

At the daily scale, the FAI may be influenced by holidays, event interventions, or data noise, resulting in pronounced short-term fluctuations. To extract its long-term variation patterns, this study applies a moving average method to smooth the time series. The aim is to reduce the impact of local anomalies on the overall trend, thereby enabling clearer identification of the seasonal evolution patterns of attractiveness (de Carvalho et al., 2020).

Let the original time series be denoted as $\{FAI_t\}_{t=1}^{T}$, the smoothed trend value $Trend_t$ is defined as follows:

$$Trend_t = \frac{1}{n}\sum_{i=0}^{n-1} FAI_{t+i} \qquad \text{(Eq.4)}$$

Here, n is the length of the sliding window, which is set to 7 in this study, representing a one-week interval for calculating the local average. For each time point, this method extracts the average attractiveness level over the following n days, thereby generating a smoothed trend sequence. To facilitate comparison between online attention and on-site visitation, Weibo check-in data were also aggregated on a daily basis and smoothed using the same 7-day moving average, resulting in check-in trend curves for each park.

The smoothed results are used to support trend structure classification analysis. By analyzing the number and distribution of peaks in each FAI curve, parks are classified into unimodal, bimodal, or multimodal types. This categorization helps reveal the temporal patterns and evolutionary trends of floral attractiveness.

Correlation analysis

To better understand the relationship between FAI and its component variables, this study applies the Pearson correlation coefficient to analyze the correlations among three time series: FAI, $total\_posts$, $flower\_ratio$. The Pearson correlation coefficient is used to measure the degree of linear correlation between two variables (Arif and Sengupta, 2021), and is calculated as follows:

$$r = \frac{\sum_{i=1}^{n}(X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^{n}(X_i - \bar{X})^2 \sum_{i=1}^{n}(Y_i - \bar{Y})^2}} \qquad \text{(Eq.5)}$$

Here, X_i and Y_i represent the values of the two time series at time i; $\bar{X}$ and $\bar{Y}$ denote the mean values of the two series, and n is the length of the time series.

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At the same daily scale, this study calculated Pearson correlation coefficients between daily check-in counts and FAI, *total_posts*, and *flower_ratio* to examine the consistency between social media–based attractiveness indicators and changes in actual visitation intensity.

Short-term FAI prediction based on LSTM

To achieve short-term dynamic prediction of FAI, this study constructs a time series regression model based on Long Short-Term Memory (LSTM) networks (Sherstinsky, 2020). The model takes daily multivariate historical data as input and outputs the FAI value for the next time step, aiming to capture day-level changes in park attractiveness. The model input is constructed using a fixed-length sliding window, with each window containing historical observations from 10 consecutive days. Input features include the smoothed FAI, normalized total post volume, holiday indicators, and others. The prediction target is the FAI value on the 11th day. To eliminate dimensional differences, all features are normalized to the [0, 1] range before training.

The LSTM network structure (*Figure 3*) consists of a single LSTM layer with 64 units, followed by a fully connected output layer (Gers et al., 2000). It consists of a memory cell c_t, three gates (input i_t, forget f_t, output o_t), and nonlinear transformations including sigmoid and tanh functions, which together regulate information flow and temporal dependency.

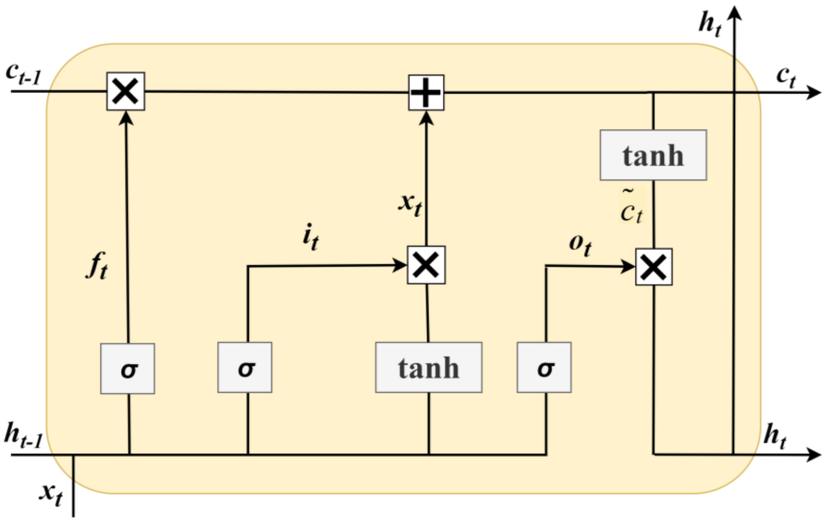

***Figure 3.** The internal architecture of an LSTM unit*

The loss function used is Mean Squared Error (MSE), and the optimizer is Adam. An early stopping mechanism is introduced during training, with 20% of the data allocated to the validation set to prevent overfitting. The predictive relationship of the model can be expressed as:

$$\hat{y}_{t+1} = f(FAI_{t-9:t}, Total_{t-9:t}, Holiday_{t-9:t}, Error_t) \quad \text{(Eq.6)}$$

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Here, $\hat{y}_{t+1}$ represents the predicted FAI value on day $t+1$. The function $f(\cdot)$ represents the nonlinear mapping based on the LSTM model. The variables in parentheses represent the smoothed FAI, normalized total post volume, holiday sequence, and the prediction residual from the previous time step within the sliding window, respectively.

Results

Overview of the data

This study collected data from January 1, 2014, to December 31, 2023. The total dataset contains 250,917 entries, of which 59,969 are flower-related and 11,542 are identified as noise. An overview of the data is presented in *Figure 4*. Among them, flower-related data account for 23.9%, while non-flower data make up 71.5%. In terms of months, March represents the spring peak, while October represents the autumn peak. In terms of weekdays, the data volume is higher on Saturdays and Sundays.

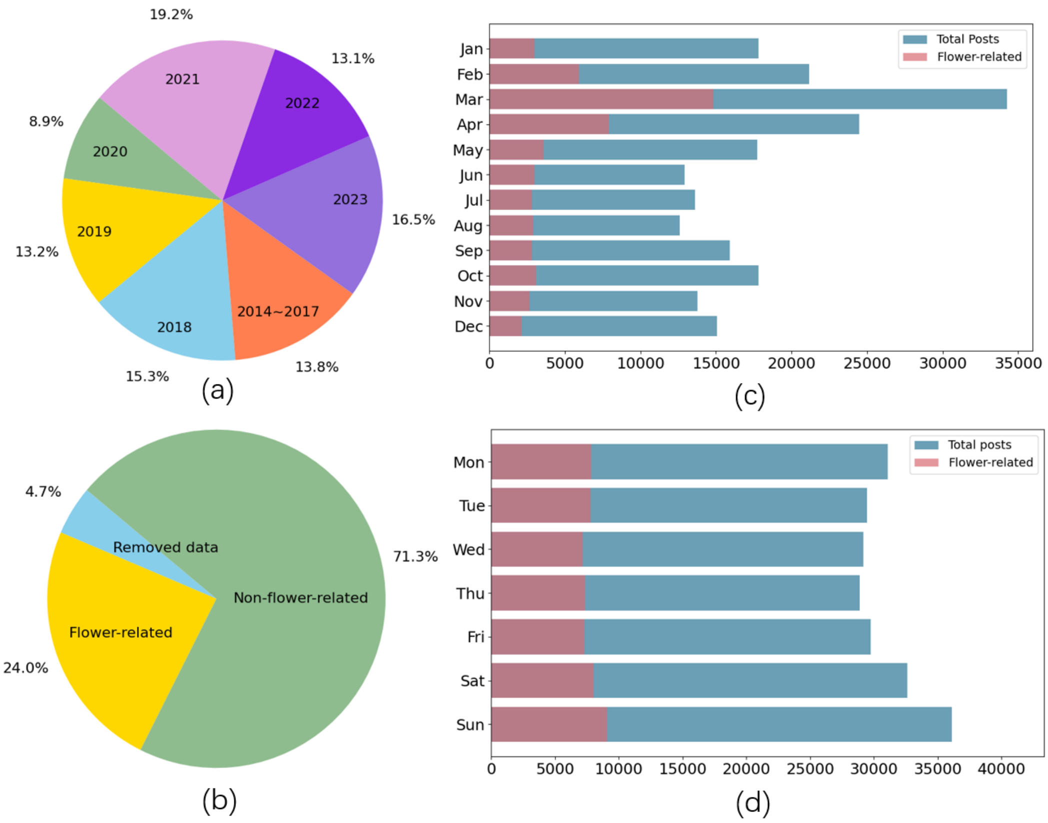

Figure 4. *Data overview*

Temporal variation and composition characteristics of FAI

The annual variation trends of flower ratio, total posts, FAI and check_ins for the ten urban parks are shown in *Figure 5*. Overall, the FAI in most parks shows clear seasonal fluctuations, typically peaking in spring (March to May), with secondary peaks observed in autumn in some parks. The bimodal seasonal pattern aligns with the known phenological seasonality of ornamental flowering in Shanghai. Using the FAI, we further

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quantify and compare differences in peak timing and magnitude across parks. Check-ins and FAI largely coincide during the spring and autumn high-value periods in most parks, indicating that periods of high FAI are temporally aligned with peaks in visitor arrivals.

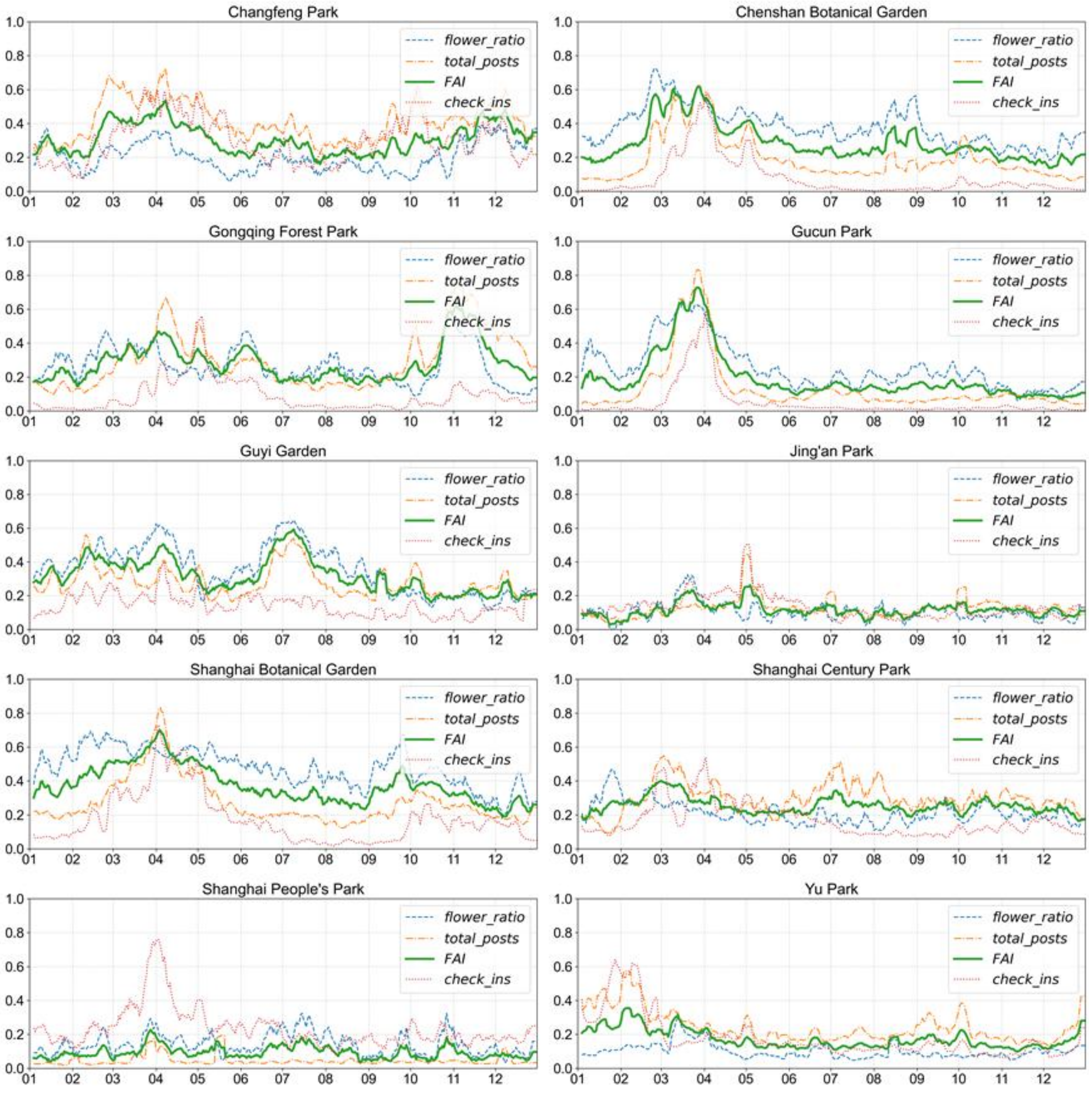

Figure 5. *Temporal variation of flower_ratio, total_posts, FAI and check_ins*

In most parks, the FAI curve exhibits a different pattern compared to its component elements. In certain periods, flower_ratio and total_posts change in the same direction. In other periods, the two show opposite trends—for example, when *flower_ratio* increases while *total_posts* decreases. In such cases, *FAI* typically falls between *flower_ratio* and *total_posts*, with smaller fluctuations than either individual indicator and a relatively stable overall trend. The FAI curves of most parks are relatively smooth, without sharp fluctuations, indicating a regulatory characteristic in response to changes in the input components.

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Correlation analysis of FAI component indicators

The Pearson correlation coefficients between *flower_ratio*, *total_posts*, and FAI are shown in *Figure 6*. The yellow bars in *Figure 6* show that *flower_ratio* and *total_posts* are positively correlated in most parks, indicating a certain level of synchronicity between visitor activity and the frequency of flower-related content. Among them, Gucun Park, Chenshan Botanical Garden, and Gongqing Forest Park exhibit relatively high correlations, reflecting a synchronized increase in both variables during flowering seasons. People's Park and Jing'an Park show weak correlations. These parks have lower data volumes, and flower-related topics are relatively independent from overall discussion trends.

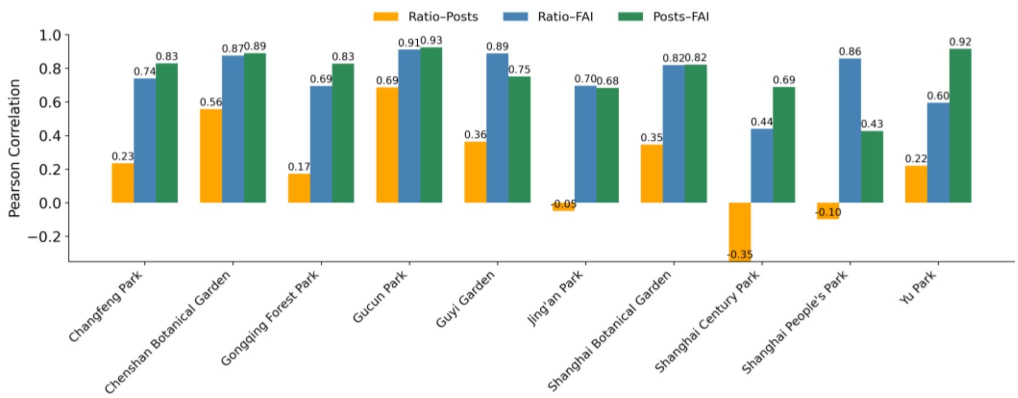

***Figure 6.** Correlation results of FAI, flower_ratio, and* total_posts

The blue bars in *Figure 6* show that FAI has a generally strong correlation with *flower_ratio*. In some parks, such as Guyi Garden, Gongqing Forest Park, and Gucun Park, the correlation coefficient exceeds 0.9, indicating that the proportion of flower-related content contributes significantly to the FAI. In contrast, in parks with lower activity or sparse flower-related content, such as Jing'an Park, the correlation is notably weaker.

The green bars in *Figure 6* show that the correlation between FAI and *total_posts* remains high in most parks. The correlation is most pronounced in Yu Garden, Guyi Garden, and Gucun Park, indicating that visitor activity is another key component of FAI in these areas.

Overall, FAI shows strong linear associations with both of its input variables, confirming its effectiveness in integrating multi-source information. The correlation between *flower_ratio* and *total_posts* is relatively weak in some parks, indicating a degree of independence in their temporal variation.

To examine the relationship between FAI and actual visitation intensity, *Table 2* presents the Pearson correlation coefficients between daily check-in counts and total_posts as well as FAI. Overall, the correlation coefficients between check-ins and total_posts mostly range from 0.3 to 0.8. In particular, Gucun Park, Chenshan Botanical Garden, Shanghai Botanical Garden, and Yu Garden show relatively high correlations (around 0.60–0.83), indicating that posting activity and visitation intensity are largely consistent in their temporal patterns. The correlation between check-ins and FAI averages around 0.4, and reaches 0.55 to 0.76 in the parks mentioned above, indicating that periods of high FAI largely coincide with peaks in visitor arrivals.

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***Table 2.** Correlations between Check-ins, FAI, and Posts*

park_name	checkins_total	checkins_FAI
Changfeng Park	0.3746	0.2880
Chenshan Botanical Garden	0.6937	0.5763
Gongqing Forest Park	0.3697	0.3096
Gucun Park	0.8250	0.7569
Guyi Garden	0.2672	0.2737
Jing'an Park	0.4706	0.3950
Shanghai Botanical Garden	0.6731	0.5737
Shanghai Century Park	0.1500	0.1714
Shanghai People's Park	0.1914	0.2206
Yu Garden	0.6056	0.5478

To identify the temporal characteristics of FAI, this study evaluates trends based on the number of major peaks observed in the annual time series. If there is one prominent peak, it is classified as a unimodal trend; if there are two, it is considered bimodal; and if there are three or more, it is defined as a multimodal trend.

To identify the dominant factors influencing FAI, this study calculates the Pearson correlation coefficients between FAI and *flower_ratio* as well as *total_posts*. If the correlation coefficient between FAI and one factor exceeds 0.7 and is at least 0.15 higher than that of the other factor, that factor is considered dominant. If both correlation coefficients exceed 0.7 and the difference between them is less than 0.15, the two factors are considered to jointly drive the FAI. If both correlation coefficients are below 0.7 or the difference between them is not significant, no clear dominant factor is identified. The trend patterns and dominant factors of FAI are presented in *Table 3*.

***Table 3.** Trend patterns and dominant factors of FAI*

Park Name	FAI Trend Pattern	FAI Dominant Factor
Changfeng Park	Bimodal	*flower_ratio* and *total_posts*
Chenshan Botanical Garden	Bimodal	*flower_ratio* and *total_posts*
Gongqing Forest Park	Bimodal	*flower_ratio* and *total_posts*
Gucun Park	Unimodal	*flower_ratio* and *total_posts*
Guyi Garden	Bimodal	*flower_ratio*
Jing'an Park	Unimodal	No Clear Dominant Factor
Shanghai Botanical Garden	Multimodal	*flower_ratio* and *total_posts*
Shanghai Century Park	Bimodal	No Clear Dominant Factor
Shanghai People's Park	Multimodal	*flower_ratio*
Yu Garden	Multimodal	*total_posts*

Trend-based results

To further evaluate the time series characteristics of FAI, this study introduces an LSTM model for predictive analysis. *Figure 7* shows the daily FAI prediction curves based on the LSTM model. The overall trends closely match the actual values, effectively capturing attractiveness changes in most parks during spring and autumn. For example, in Gucun Park, Gongqing Forest Park, and Chenshan Botanical Garden, the predicted curves during peak flowering periods almost overlap with the actual trends,

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demonstrating strong temporal responsiveness. In parks with weaker fluctuations, such as Jing'an Park, the predicted curves show slight deviations, but the overall structure remains largely consistent.

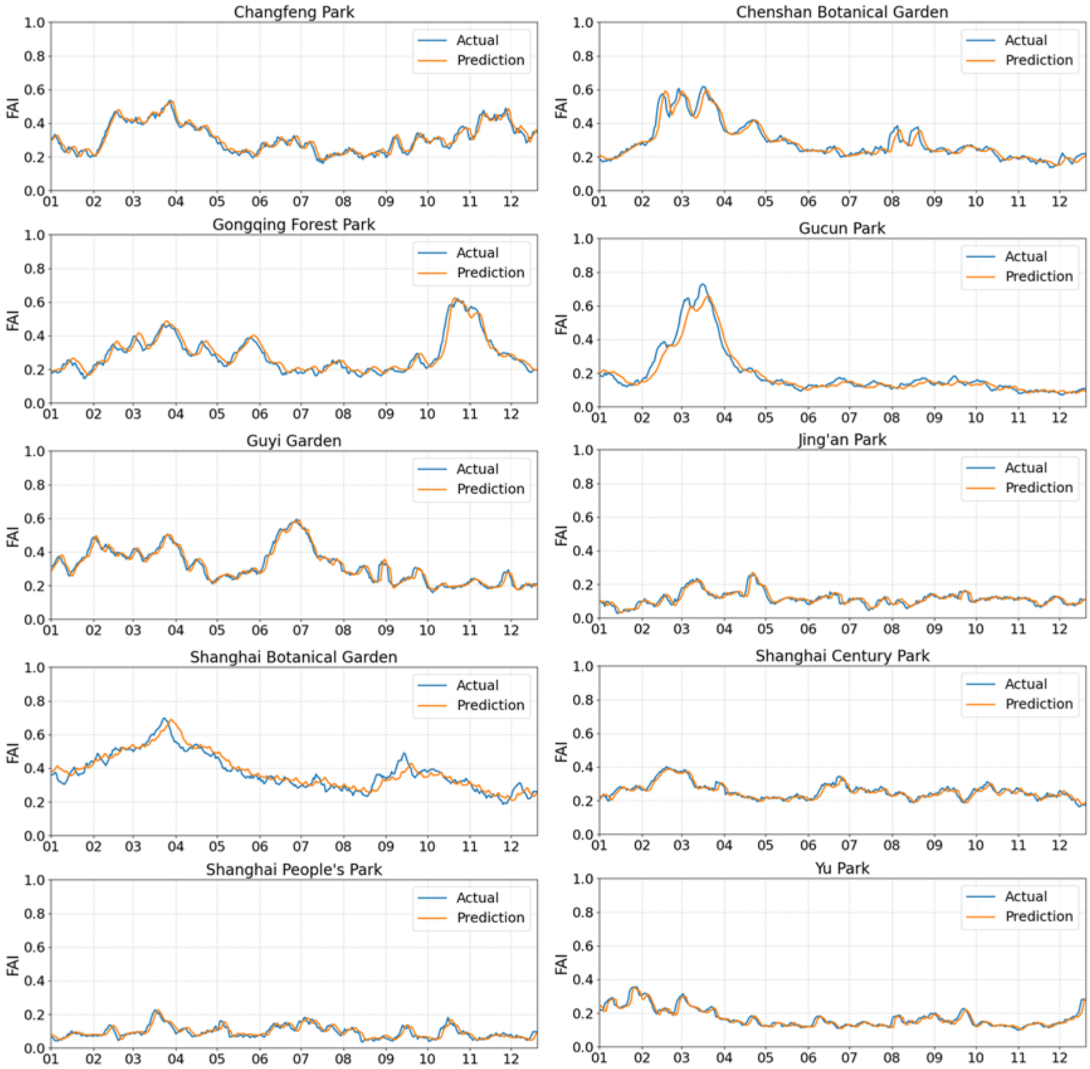

Figure 7. *Daily FAI prediction curves based on the LSTM model*

The model performance metrics for FAI time series prediction across urban parks are presented in *Table 4*. For most parks, the coefficient of determination (R^2) exceeds 0.90, and the mean absolute error (MAE) remains below 0.02, indicating that the model has stable fitting capability. For example, Gongqing Forest Park achieves an R^2 of 0.956, with an MAE of only 0.0176. In contrast, Jing'an Park has an R^2 of 0.826, indicating relatively weaker performance due to low variability in the original data and a higher proportion of noise.

To examine whether weather conditions can be integrated into the predictive model, this study extends the original LSTM inputs by incorporating daily meteorological variables for 2022. Specifically, daily mean temperature and precipitation are added to predict FAI. The comparative prediction performance between the model without weather variables and the model incorporating weather variables is shown in *Table 5*. *nw* indicates

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the LSTM model without weather variables, and *ww* indicates the LSTM model with daily meteorological variables as additional inputs. The results show that, among the ten parks, four parks exhibit overall improvements across all four metrics—MSE, MAE, MAPE, and R^2. Two parks perform similarly to the baseline model, while the remaining four parks show slightly increased prediction errors after incorporating weather variables, accompanied by a slight decrease in R^2. Overall, under the conditions of this study, the effects of incorporating weather variables vary across parks and do not show a consistent improvement trend.

Table 4. *Model performance metrics for FAI time series prediction in urban parks*

Park	MSE	MAE	MAPE	R^2
Changfeng Park	5.83E-04	1.97E-02	6.81	0.92
Chenshan Garden	7.20E-04	1.80E-02	6.11	0.94
Gongqing Park	5.22E-04	1.76E-02	6.41	0.96
Gucun Park	1.31E-03	2.40E-02	11.92	0.94
Guyi Garden	4.96E-04	1.65E-02	5.36	0.95
Jing'an Park	2.83E-04	1.18E-02	11.61	0.83
Botanical Garden	1.49E-03	3.00E-02	8.31	0.87
Century Park	2.55E-04	1.27E-02	5.00	0.88
People's Park	3.32E-04	1.41E-02	16.24	0.75
Yu Garden	2.93E-04	1.18E-02	6.59	0.91

Table 5. *LSTM prediction performance with and without weather variables*

	MSE		MAE		MAPE		R^2	
	nw	*ww*	*nw*	*ww*	*nw*	*ww*	*nw*	*ww*
Changfeng Park	**4.04E-02**	7.32E-02	**3.30E-02**	5.99E-02	**27.4728**	60.2520	0.90	0.67
Chenshan Garden	**2.88E-02**	2.93E-02	**2.23E-02**	2.27E-02	13.5266	**12.8219**	0.90	0.89
Gongqing Park	3.47E-02	**3.12E-02**	2.80E-02	**2.56E-02**	22.9535	**20.6168**	0.79	**0.83**
Gucun Park	3.61E-02	**2.65E-02**	2.81E-02	**2.00E-02**	19.0943	**14.1582**	0.93	**0.96**
Guyi Garden	3.54E-02	**3.25E-02**	2.84E-02	**2.61E-02**	29.3044	**26.7413**	0.90	**0.91**
Jing'an Park	2.22E-02	**2.14E-02**	**1.24E-02**	1.25E-02	**26.3615**	28.8276	0.80	**0.81**
Botanical Garden	**3.84E-02**	8.93E-02	**3.06E-02**	7.30E-02	**22.7077**	76.5807	0.90	0.46
Century Park	2.94E-02	**2.11E-02**	2.23E-02	**1.55E-02**	15.2837	**11.6110**	0.74	**0.86**
People's Park	**3.01E-02**	3.07E-02	**2.23E-02**	2.43E-02	**58.0348**	74.6798	0.81	0.80
Yu Garden	**1.32E-02**	1.33E-02	**9.79E-03**	9.98E-03	11.8292	**11.7176**	0.94	**0.95**

Temporal and spatial distribution characteristics of floral attractiveness

To reveal the temporal variation of floral attractiveness throughout the year and its spatial differences across parks, this section presents two heatmaps based on social media data. It separately analyzes the attention intensity of different flower types across months and the floral attractiveness performance of the ten urban parks over time, as shown in *Figure 8*. The left panel shows the peak attention periods for different flower types throughout the year, while the right panel illustrates the monthly variation in floral attractiveness across the parks.

In terms of temporal distribution, most flower types exhibit clear seasonality. Cherry blossoms receive peak attention in March and April, making them the dominant flowers of spring. Plum blossoms gain increased attention in February and March, reflecting their

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early-spring blooming pattern. Lotus and water lilies peak in July and August, representing typical summer flower species. Some flowers, such as roses, have a more dispersed temporal distribution but generally receive lower overall attention.

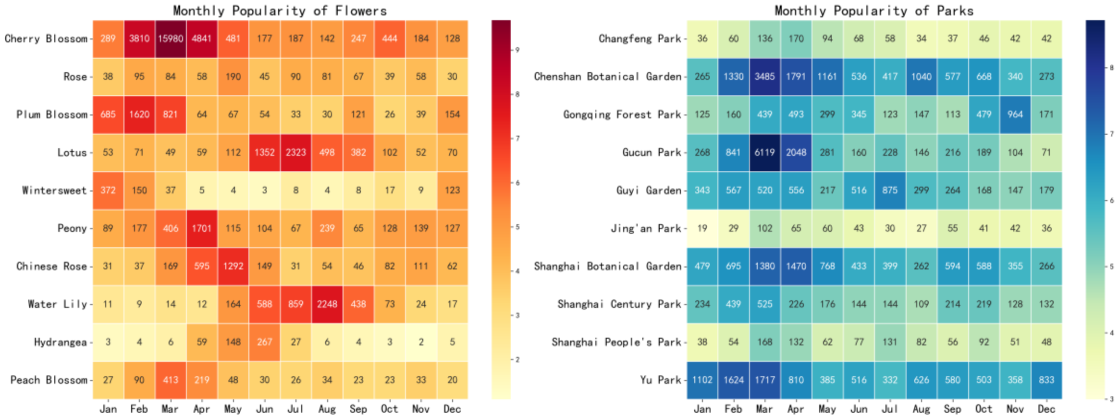

Figure 8. *Heatmaps of floral popularity by urban parks and by month*

In terms of spatial distribution, there are significant differences in floral attractiveness among the parks. Gucun Park and Chenshan Botanical Garden exhibit prominent springtime popularity, peaking in March, primarily driven by cherry blossoms. Shanghai Botanical Garden and Gongqing Forest Park display a more prolonged period of floral popularity, reflecting greater diversity in flower species. Century Park experiences increased attention in May and July, primarily driven by Chinese roses and roses. Yu Garden is active in early spring due to plum blossoms. In contrast, Jing'an Park and People's Park exhibit lower overall popularity, lacking distinct seasonal peaks.

Discussion

Effectiveness and performance of the FAI

As an integrated attractiveness indicator, the FAI effectively reflects the public's overall attention to floral landscapes in urban parks by combining *flower_ratio* and *total_posts*. Compared to single-dimensional measures, the FAI demonstrates greater trend stability. Especially when the raw data fluctuate sharply and flower-related attention diverges from overall visitor volume, the FAI smooths conflicting information and maintains consistent trend representation.

This characteristic enhances the stability of the FAI in seasonal trend analysis, effectively reducing the impact of sporadic data fluctuations and more accurately identifying peak periods of floral appreciation. This is especially crucial in multi-park comparisons, as significant differences exist in floral arrangements and event schedules across parks. Compared to single-dimensional indicators, the FAI is better suited as a core variable for cross-sectional comparisons and dynamic monitoring.

The construction of the FAI provides a new perspective for quantitative modeling of urban floral attractiveness. Traditional park evaluations often emphasize absolute visitor numbers or social media popularity, while neglecting the importance of "relative attention" as a key metric (Cats and Ferranti, 2022; Chuang et al., 2022). By integrating

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two variables from different sources and scales, the FAI offers a method for attractiveness modeling that balances both intensity and significance (Chang and Olafsson, 2022).

The FAI possesses strong scalability and transferability, with a structure that allows the incorporation of multimodal data features. For example, it can integrate flower recognition results from images, visitor dwell behavior, or seasonal environmental data to form more complex composite indicators, adapting to richer urban ecological application scenarios. This makes it suitable not only for current text-based analysis tasks but also extendable to broader smart tourism and perception ecology research. The FAI is not used to identify the biological onset of flowering for individual species. Rather, it captures the timing and evolution of flowering seasons at the park scale, as reflected by collective visitor attention and posting activity.

This study uses Weibo check-in data to indirectly validate the temporal patterns of FAI. Correlation analysis shows that, in most parks, daily check-in counts are moderately to strongly correlated with both posting volume and FAI at the daily scale, and their high-value periods broadly correspond to major flowering seasons and peaks in visitor arrivals.

Temporal and spatial variations in floral attractiveness

Floral attractiveness in urban parks exhibits significant temporal and spatial differences. Based on the temporal variations of FAI and heatmap analyses, this study finds that different parks exhibit clear seasonal fluctuation patterns and regional distribution characteristics in floral attractiveness across months. Floral popularity in Gucun Park and Chenshan Botanical Garden is concentrated in early spring, mainly driven by the Cherry Blossom Festival. In contrast, Shanghai Botanical Garden exhibits multiple peaks in popularity throughout the year, reflecting greater floral diversity and event frequency. These differences are influenced not only by the phenological rhythms of plants but also by park positioning and management strategies (Zeng et al., 2024).

From a temporal perspective, most parks exhibit FAI peaks concentrated in March to May and September to November, corresponding to the main flowering seasons in spring and autumn. Jing'an Park shows a prominent FAI peak in June and July, mainly influenced by the blooming of lotus flowers, creating a short-term summer popularity peak. These seasonal variations align closely with the climatic rhythms of the Shanghai region and the flowering cycles of the main ornamental plants. This indicates a strong coupling relationship between public attention behavior on social media and ecological processes (Song et al., 2020). Together with the FAI, these well-known seasonal patterns are transformed into comparable time series, allowing us to quantify differences in the strength and timing of floral attractiveness across parks.

From a spatial perspective, there are significant differences in the overall FAI levels among the parks. Small, comprehensive parks in central urban areas, such as People's Park and Jing'an Park, often experience increased popularity during holidays or special events due to their geographic location and high visitor density (Zhou et al., 2024). In contrast, large suburban parks or botanical gardens rely more on themed events such as flower exhibitions to maintain their attractiveness. For example, Chenshan Botanical Garden and Gongqing Forest Park achieved significant short-term peaks by intensively showcasing spring flowers such as cherry blossoms and roses.

In culturally themed parks, the temporal rhythm of floral attractiveness reflects strong humanistic characteristics. For example, Yu Garden receives sustained attention in winter due to wintersweet and plum blossoms, reflecting not only seasonal landscape changes but also the influence of festival culture and traditional aesthetics (Cheng et al., 2022).

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Short-term predictability of floral attractiveness trends

Short-term variations in floral attractiveness are of great significance for urban park management. Timely identification of potential popularity peaks can provide data support for event planning, visitor management, and promotional efforts (Štekerová et al., 2022). Compared to using only total post volume or the proportion of flower-related posts as the prediction target, the stability and integrative nature of the FAI enhance the model's ability to capture fluctuation trends. Especially when dealing with nonlinear disturbances, holiday impacts, and seasonal transitions, the model is still able to maintain continuity and reliability in its predictions.

From the performance across different parks, those that host concentrated floral events or feature a distinctive single-flower brand tend to show more pronounced FAI prediction results. For example, the cherry blossom popularity trends in Gucun Park and Chenshan Botanical Garden exhibit strong regularity and large fluctuations, making it easier for the model to learn their short-term patterns. In contrast, comprehensive parks with a greater variety of flowers and more evenly distributed popularity tend to exhibit a certain level of uncertainty. Although the prediction errors are slightly higher, they remain within an acceptable range (Chen et al., 2024).

The results on short-term predictability indicate the presence of quantifiable behavioral patterns in social media data (Chaudhary et al., 2021). These patterns are not only driven by biological seasonal rhythms but are also influenced by user posting habits, the intensity of event marketing, and weather conditions. Therefore, short-term prediction results can be used not only for technical time series modeling but also as empirical evidence for understanding the social response mechanisms to urban nature experiences.

Implications for urban park planning and visitor management

The FAI index developed in this study holds practical value for park management applications. From a dynamic monitoring perspective, the FAI can accurately reflect visitor attention to floral landscapes without relying on on-site surveys. For park managers, this social media-based approach to measuring attractiveness helps identify potential fluctuations in visitor flow across different time periods. Based on this, timely adjustments can be made to security, crowd guidance, and transportation coordination (Georgiadis et al., 2020; Gong et al., 2020).

The spatial variation in floral attractiveness also provides useful insights for park management strategies (Tomitaka et al., 2021). For example, Gucun Park relies on a single type of flower to create prominent seasonal peaks. Park managers can design supporting activities—such as exhibitions, performances, and photo spots—centered around the blooming period to enhance visitor experience and extend their stay. In contrast, comprehensive parks like the Shanghai Botanical Garden, which exhibit stable floral attractiveness curves throughout the year, should focus on enhancing multi-flower combinations and seasonal transitions to maintain sustained public attention and ecological appeal (Giovanetti et al., 2020).

At the application level, FAI can serve as an early warning indicator for floral landscape management and visitor scheduling. Management authorities can use FAI and its short-term forecasts to identify high-attractiveness periods in the coming weeks and adjust cleaning, security, and guidance resources accordingly, especially during holidays and peak flowering seasons. By comparing FAI curves across different parks, it is also possible to identify parks with similar resource conditions but relatively lower

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attractiveness. These parks can then be prioritized for improvements in floral arrangement and activity design. The temporal patterns of FAI can also support the scheduling of flower exhibitions and seasonal events, allowing promotion and operations to better align with visitors' actual flower-viewing demand rather than relying solely on experience.

The concept of the composite indicator represented by the FAI also offers an expandable framework for data-driven decision-making in smart park systems. It is not limited to the current use of flower-related post counts and proportions, but can also incorporate additional dimensions such as image recognition, path data, and sentiment analysis. It can play a greater role in evaluating the ecological attractiveness of urban parks, modeling visitor behavior, and optimizing scene design (Mousazadeh et al., 2023; Mohamed and Kronenberg, 2025).

Limitations and future prospects

This study proposed a modeling approach for floral attractiveness and validated the feasibility of index construction, trend analysis, and short-term prediction. This study did not conduct systematic field observations of visitor flows and instead relied on Weibo check-in data as a behavioral proxy. Future work should incorporate targeted on-site observations during key flowering seasons to further validate the FAI-based approach.

Future research can further expand at the data level by incorporating image content, comment semantics, or location information to gain a more comprehensive understanding of visitor attention (Deveci et al., 2023; Lu et al., 2023). Methodologically, multimodal learning or causal inference models can also be explored to further reveal the relationship between floral landscapes and visitor behavior (Runge et al., 2023; Aziz et al., 2025). In addition, integrating the Floral Attractiveness Index with offline operational data—such as ticket sales or visitor flow monitoring—will help build decision-support tools that are more closely aligned with management practices. This, in turn, can promote the intelligent management of urban green spaces.

Conclusion

This study constructed a Floral Attractiveness Index based on social media data from Weibo and Ctrip, integrating the proportion of flower-related content and visitor activity to capture the dynamics of public attention toward floral landscapes in urban parks. Focusing on ten representative parks in Shanghai, the study systematically analyzed the temporal variations, spatial differences, and key influencing factors of the FAI. The results show that the FAI in most parks exhibits regular seasonal fluctuations, with spring being the primary peak period, while some parks also show notable activity in autumn. Correlation analysis identified different mechanisms underlying floral attractiveness across parks, including activity-driven, content-driven, and dual-factor co-driven types. The LSTM prediction results further validated the stability and applicability of the FAI in capturing short-term trends. As an integrative indicator, the FAI effectively reflects the temporal evolution and spatial distribution of floral attractiveness. It holds practical potential for dynamic monitoring and refined management, and offers methodological support for expanding the use of social media data in urban ecological perception research.

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DOI: http://dx.doi.org/10.15666/aeer/2401_12791299

Acknowledgements. This work was supported by the Huaiyin Normal University commissioned project *Evaluation System for the Influence of Urban Park Plant Landscapes Based on Social Media* (46ZXJ01).

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