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RESEARCH ARTICLE

Public Perception of City Image Hotspots Based on Social Media: A Case Study of Nanjing, China

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ABSTRACT City image is an important element in the design of urban features. Big data from social media has become a new way to perceive city image characteristics. Taking Nanjing (China) as a case study, we use social media data from the "Little Red Book" and "Sina Weibo" (similar to Twitter in China) and employ deep learning methods, multisource data semantic analysis, sDNA, and geographically weighted regression to analyze three aspects: the spatial distribution of hotspots, perception characteristics, and influencing factors. The hotspots are located in Nanjing's old city, centered on Confucius Temple, and extend outward in a circular pattern. Regarding perception characteristics, the key characteristics that define the old city are "heritage monuments", "long history", and "culture". The high functional perception area converged around the central urban area. The spatial distributions of closeness and betweenness under traffic perception showed opposite trends; emotional perception was mainly positive. Compared with visual and emotional perception, functional and traffic perception have greater impacts on city image hotspots. Our study constructs a model of city image perception from a new perspective. This approach bridges the gap that traditional city image research focuses only on objective environment descriptions and lacks subject-object relationship analysis, which can provide scientific value for decision makers in urban design management.

INDEX TERMS City image, social media, spatial perception, big data, Nanjing.

I. INTRODUCTION

To improve the appearance of the community, planners need to know how the public evaluates the cityscape: their evaluative image of the city [1]. City image is a comprehensive embodiment of the impressions, opinions, cognitions, evaluations, and feelings of people. It can be expressed through pictorial and textual means [2], [3]. With respect to city image, people always think of Kevin Lynch's book "The Image of the City" published in 1960, one of the most influential theories on spatial cognition and behavioral geography ever written [4]. Lynch presented five elements of a cognitive map through a mental map and interviews [5], which triggered a research upsurge in city image. Since then, many scholars have improved upon Lynch's theory and deepened it [6]. Some publications are dedicated to verifying Lynch's study in practical applications and have been conducted in the United States, Europe, and Asia [1], [7], [8], [9], demonstrating the effectiveness of building a city image on the basis of five elements. Furthermore, the research perspective of city image in various countries has become multidimensional, and the conceptual system [10], historical form and evolution process [11], spatial perception [12], and elements [13] have been explored.

There has been increasing interest among urban planners in understanding how people perceive the environment. Cultural and physiological factors can affect the perception and cognition of a city's image.

With respect to research content, previous studies have revealed significant links between public perceptions and

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the use of public spaces [14]. Some studies have related the presence of specific elements, such as static elements in the urban built environment, architectural forms, public facility support, parks, green spaces, and land use, with perception [14], [15], [16]. Dynamic elements affect urban perception; for example, the quality, quantity, distribution, and strategic planning of roads affect travel efficiency, safety, and comfort [17]. Kanwal et al. supported this claim by confirming a positive correlation between roads and community satisfaction through extensive questionnaire data [18]. Moreover, urban landscapes are experienced by their users largely through visual perceptions [14]. This has been explored in the literature, which shows that visual perceptions can influence the intensity of the use of public spaces [19]. Furthermore, Akgün et al. [20] investigated 150 tourists on the last day of their tours and reported that the cognitive image of Istanbul was a multidimensional construct composed of attraction, infrastructure, atmosphere, and value variables. Nostalgic emotion was positively related to affective destination image and all components of the cognitive destination image of Istanbul. The results suggest that emotion could also affect public behavioral intentions via destination image. In addition to the factors mentioned above, social media can affect image perception of the environment [21] and present a novel and unprecedented method of achieving ''social perception'' in urban environments [28]. It is a growing and comprehensive but still incomplete source of data on people–nature interactions [29]. Good image perception is an effective way to increase the popularity of tourist attractions. Tourist photos are important materials for understanding behavior and exploring perceptions of destinations [22]. Stories and images in travel logs vividly create the essential destination image for local marketing. Travel logs are a representation of the destination experience that public and private tourism organizations can use in their promotional and marketing programs to enhance the perception of the destination image [23]. Previous studies have made important contributions to exploring the factors that influence the subjective feelings of individuals with respect to the objective environment. They tend to focus on the effects of single-level elements in the urban built environment on perception rather than integrating static elements with dynamic elements. Most studies simply explore the characteristics of the objective environment from the spatial structure, ignoring the individual's perception of the nonmaterial aspects [24]. Our study unites dynamic and static elements to evaluate urban built environments and delves deeper into how these surroundings influence city perceptions.

With respect to research methods, previous studies collected public behavior and opinions via traditional methods. Interviews, questionnaire surveys, and sketch cognitive maps are labor intensive, time-consuming, do not scale well, and have limited space for free expression [25], [26]. In recent years, social media services have provided a more convenient way to acquire massive amounts of data [27], which is important for studying the distribution of popular landmarks. Social media data and social media analytics leverage crowd-sourced public opinion rather than those of a targeted and directed audience. Global internet users easily connect and share up-to-date information and real-time content in a virtual world. Check-in activities affect the reconstruction of the social networking space and are indispensable for understanding the rules of human behavior [27]. Previous studies explored the relationships between city image elements and human perception through deep learning and network data [28], evaluated differences in city images on user-generated travel photos [29], reported perceptions of city images via social media [2], and analyzed the spatial distribution characteristics of public emotions and different types of places via big data from Sina Weibo [24]. To some extent, previous studies provided a new technique for evaluating city image perception, helped bridge the gaps between quantitative and qualitative methods, and compensated for the lack of traditional research samples [25]. However, relevant publications have focused only on a single analysis of photos or user-defined textual information. The formation process of the city image from the dual dimensions of subjective perception and the objective environment remains largely unknown [30]. Furthermore, most studies, especially those on structural city images, have largely described only the results and characteristics exhibited by big data at the overall spatial level and have used Lynch's theory for argumentation without conducting a more in-depth analysis. The roles of individual subjective perceptions and the objective environment, as well as the influence mechanism of perceptual elements, are ignored [24].

With respect to the data source, flicker check-in data [31], Panoramio photo data [32], Instagram photo data [33], Twitter check-in data [34] and Sina Weibo check-in data [35] have been used for city image perception in recent years. However, the majority of these platforms lack the distinctive behaviors and preferences that characterize the Chinese market and its user base in their endeavors. Until November 2023, the ''Little Red Book'' (https://www.xiaohongshu.com) and ''Sina Weibo'' (https://weibo.com) had more than 200 million and 500 million active monthly users, respectively [36]. The large number of active users is sufficient to support our study. Moreover, the platform allows the sharing of emotional perceptions and tagged photographs (with geo-reference data), aggregating an enormous crowd-sourced recommendation database. Each user can be considered a ''sensor'', capable of perceiving the political, economic, social, cultural, and environmental aspects of the city. These perceptions are shared through various means, such as text, images, emojis, and labels, using the ''Little Red Book'' or ''Sina Weibo''. This approach compensates for the gaps in traditional studies that focus on the perception of material form and ignore culture and ideology.

The integration of multisource data can compensate for the sample deviation of data. Public perception cannot be identified using only one type of the data [37]; for example, in terms of user reach, Weibo boasts a more extensive penetrated user base than the Little Red Book does [38]. The demographic characteristics of the users are characterized by a broader spectrum of age groups and a wider geographic spread. The reach of Weibo is further underscored by its significant engagement metrics, with higher levels of active daily and monthly users. Although the Little Red Book has immense popularity among the younger generation, its overall market coverage remains less extensive than that of Weibo. The perceptions of the urban environment on the two platforms presented distinct focal points. The Little Red Book emphasizes the nuances of lifestyle and consumer experiences, crafting a narrative around personal journeys and tastes [39]. In contrast, Weibo presents a kaleidoscope of content that spans a wider array of topics. With respect to the timeliness and depth of information, the public perception of Weibo tends toward instant sharing and rapid dissemination [40]. While this results in a broad spectrum of information, the depth of insight might not match the breadth. However, the comments of the Little Red Book are more in depth. The platform is replete with detailed travelogues and guides that users contribute, which serve to enrich and refine the image of the destination.

With respect to the research area, public perceptions and preferences for urban nature tend to vary across different site-specific factors. The interactive relationship, process, and result between public subjective perception and the objective environment is the central connotation of the city image, with the objective physical environment as the object [41]. Therefore, case studies are vital for identifying local differences. Previous publications on the importance of urban built environments have been conducted in America, Europe, Australia, [12], [42], [43] and Southeast Asia [44], [45]. There is a knowledge gap in terms of public perception, infrastructure, and space in East Asia [46]. To fill this gap and detect more valuable information from built-up urban environments and public emotions, we take "how individual cognition and built environments affect the city image" as the core question. The specific objectives are (1) to establish Nanjing city image hotspots by mining data from the Little Red Book and Weibo; (2) to analyze the perceived characteristics of city image hotspots; and (3) to explore the feasibility of using the GWR4.0 model in the study of public perception and the objective environment in the urban image attraction area.

II. MATERIALS AND METHODS

The operational methods are described here (Figure 1): (1) collection and processing of check-in data, POI data, road network, and street view images; (2) research on subjective perceptions and objective environment characteristics and the distribution of city images; (3) construction and evaluation of the geographically weighted regression model via ArcGIS 10.8.2; and (4) analysis of the results, including exploration of the correlations among subjective perceptions, the objective environment, and city image hotspots.

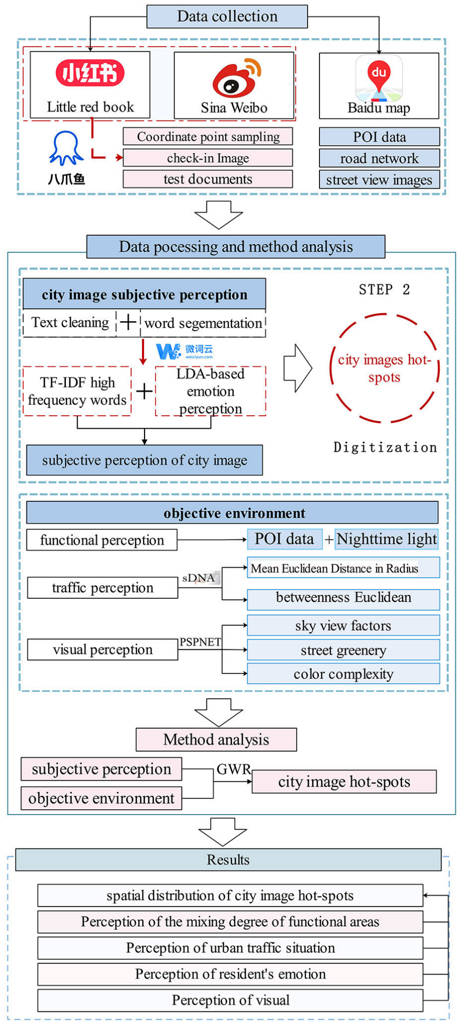


FIGURE 1. Technology flow chart.

A. STUDY AREA

Nanjing, the capital of Jiangsu Province, is one of the most important cities in the Yangtze River Delta, China. It is located in eastern China and has an east longitude of 118° 22′ –119° 14′ and a north latitude of 31° 14′ –32° 37′. As one of the four ancient capitals and the second commercial center in eastern China, Nanjing has a long history and abundant culture. Its social and economic development has been at the forefront of national attention, with a total population of approximately 9.5 million. In addition, Nanjing strived to become a happy and livable city during the 14th 5-year plan. The functional layout, efficient use of facilities, and environmental quality may differ across areas. The subjective perceptions of urban residents are more likely to reflect these differences in their daily activities. The "Nanjing Land Space Master Plan" (2021-2035) delineates the boundaries of the central urban area. The region boasts a substantial population, abundant natural resources, excellent infrastructure, and efficient transit systems and is the main gathering area of urban function. Given that urban development within the central urban area is mature, the built-up area and the population are mainly distributed in this area. Therefore, the Nanjing central urban area is taken as the main study area (Figure 2).

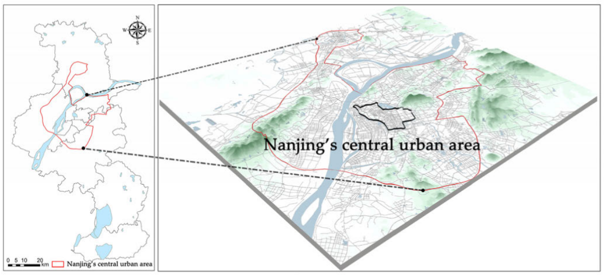


FIGURE 2. Study area.

B. DATA SOURCE AND PROCESSING

1) CHECK-IN DATA

Residents' check-in data were retrieved via the "Little Red Book" (https://www.xiaohongshu.com, accessed from 19 June 2020 to 21 September 2023) and Sina Weibo (https://m.weibo.cn/, accessed from 19 June 2020 to 21 September 2023) via assigned tags ("Nanjing check-in", "Nanjing travel", "Nanjing Citywalk"). A total of 205,091 actual distribution sites of check-in data were collected. The geographic distribution of the "check-in" data was further processed via ArcGIS 10.8.2 software. The process included the following steps: first, information was obtained on user check-in data points through the official open API interface of Sina Weibo, including geographic location. The exact longitude and latitude of each Little Red Book collection site were manually selected via Bigemap software. Second, whether the reported latitudes and longitudes matched the collection sites was checked one by one; then, we corrected the deleted duplicate and irrelevant content. Finally, a total of 35,569 instances of geotagged "check-in" data were collected, 33,908 of which were within the central urban area of Nanjing.

2) POI DATA

More than 328,849 POIs were obtained from 12 December 2022 to 30 December 2022 via the Amap (Version 13.07.0.2160) geolocation service API (https://ditu.amap.com/), of which 235,417 were within the central urban area. The POI data are divided into 23 categories on the basis of their business services: high-tech companies; traditional manufacturing industry; real estate; catering and entertainment; education and health care; finance; and insurance.

3) NIGHT-TIME LIGHT TIME

Nighttime light (NTL) makes people's lives more convenient [47] and helps make pedestrians feel safe and comfortable while walking at night [48]. The integration of night light remote sensing and public perception provides a new method for the sustainable urban development of light environment planning. An extended time series (2022-2023) of global NPP-VIIRS-like NTTL data (Version 5.0) was derived from the Yangtze River Delta Science Data Center, the National Earth System Science Data Sharing Infrastructure, and the National Science & Technology Infrastructure of China (http://geodata.nnu.edu.cn/) (https://dataverse.harvard.edu/dataset.xhtml?persistentId =doi:10.7910/DVN/YGIVCD). We extracted the time series of nighttime light data from 2022-2023 for Nanjing by overlapping the administrative boundary map of the processed nighttime light images with a spatial resolution of 15 arcseconds under the WGS84 coordinate reference system.

4) STREET VIEW IMAGES

We downloaded a total of 9364 street-view images from the Baidu map (https://map.baidu.com/) and then extracted the latitude and longitude of all the sampling points as one of the input parameters of the street-view image crawling script. The collected street-view images in the four directions were stitched together (Figure. 3): front, back, left, and right, each of which covers 90°, and the pitch angle (pitch) was set at 0°.

FIGURE 3. Acquisition of multitemporal panoramic images.

5) ROAD NETWORKS

The road network dataset was obtained from the geospatial data cloud (https://www.gscloud.cn/, accessed on 12 August 2023). After the remote sensing map was intercepted, the road network was digitized as vector data in ArcGIS 10.8.2. The road network included a total of 16,961 roads, of which 8,760 roads were obtained in the central urban area. The data were vectorized and preprocessed.

C. PERCPTION DATA AND PROCESSING

1) FUNCTIONAL PERCEPTION

The "mixing degree of functional areas" and "night-time light" were selected as indexes to quantify functional perception [49]. The Shannon diversity index (SHDI) can measure the degree of imbalance in the distribution of geographical elements and characterize the spatial homogeneity or heterogeneity of urban space. The level of the SHDI can reflect the equilibrium degree of urban land use (Eq. 1). A higher SHDI corresponds to more types of land use with different functions, richer urban functions, and a higher degree of mixing. In our study, there are 23 types of data ($n = 23$), and the number of each type of POI is Pi ($i = 1$, Author Name:

Preparation of Papers for IEEE Access (February 2017) 5 2…,23). We identified and analyzed the spatiotemporal characteristics of the degree of functional mixing of land use in the central urban area via ArcGIS 10.8.2.

$$SHDI = -\sum_{i=1}^{n} (P_i \times lnP_i) \quad (1)$$

2) VISUAL PERCEPTION

A pyramid scene phrase network (PSPNet) was used to segment street view images. PSPNet introduces a pyramid-pooling module, which performs context aggregation on different regions, improves the ability to use global context information, and increases the reliability of the final prediction. The flowchart used to segment the street view images is shown in Figure 4. The PSPNet model trained on the ADE20k dataset [50] was used based on an open source project (https://github.com/eddy4112/PSPNet-ADE20k). The ADE20k dataset contains 20,210 images in the training set, 2000 images in the validation set, and 3000 images in the testing set. There are a total of 3169 class labels annotated, among which 2693 are objects and other classes, whereas 476 are object classes. Then, from the segmentation results, a CSV (comma separated values) file is generated that contains the image proportions of the 150 categories, including roads, buildings, plants, skies, cars, and pedestrians. We extracted street greenery information and the sky view factor from the panoramic street-view images, and the color complexity value was calculated via OpenCV.

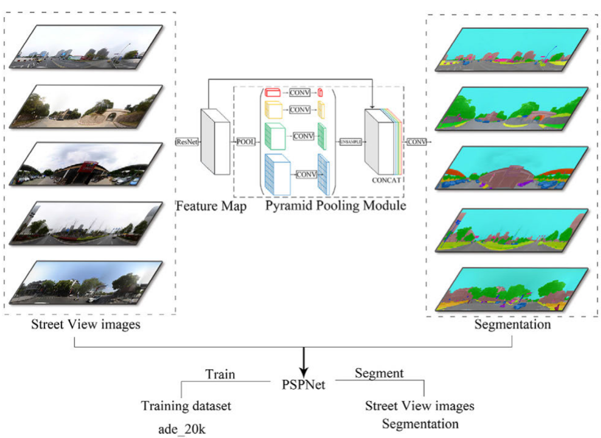


FIGURE 4. The workflow of street view image segmentation.

3) EMOTION PERCEPTION

The text sentiment analysis model is built according to the key task of feature selection and extraction. Geotagged comments on social media are utilized to create an emotional map. First, useful comment text was collected from the "Little Red Book" and "Sina Weibo" via a web crawler. Second, preprocessing and cleaning operations are performed. Through regular expression-based text replacement, all documents are cleaned by removing unwanted characters such as tags, punctuation marks, emoticons, special symbols, and URL links. It is necessary to remove data that do not reflect subjective opinions and contain only blank text, such as images and videos. Then, a Chinese text segmentation tool named Jieba, which is an open source and popular Python package (https://pypi.python.org/pypi/jieba), provides functions for Chinese word segmentation, splits the text information, and matches each word with the keywords about the environment corpus, which we set in advance for text filtering. Third, we extracted keywords and phrases from the test and classified them as positive or negative; the sentiment classification determines the tourist sentiment from their comment texts via "weiciyun" (www.weiciyun.com). Finally, we pack the resulting sentiment analysis data and pretrain the sentiment analysis package with the BERT model of the ModelSail platform to improve the accuracy of sentiment analysis. The precision, recall, and F1 score are used as evaluation metrics. Precision represents the proportion of positive samples that are correctly predicted [29]. Furthermore, ArcGIS was used to visualize the geographic spatial data of different emotional types and values and draw a flow chart and emotion map.

4) TRAFFIC PERCEPTION

The road network dataset was obtained from the geospatial data cloud (https://www.gscloud.cn/, accessed on 12 August 2023). Spatial Design Network Analytics (sDNA version 4.0.4) [51] was selected as a computing tool to analyze central indicators such as connectivity, closeness, and betweenness [52]. Our paper selected closeness and betweenness by comparing the situation under different search distances to analyze the road network in the central urban area. The search distance was set to 1000 m, 3200 m, 6000 m, and 8500 m before a global scope search was performed. The analysis parameter does not set any weight properties for the time being. A path with high closeness has high accessibility and is easier to reach a further place; the higher the degree of betweenness is, the more likely it is that an area will be passed.

D. CORRELATION AND REGRESSION ANALYSIS

1) KERNEL DENSITY ANALYSIS

Kernel density analysis was used to determine the spatiotemporal distribution characteristics of popular attraction sites. Kernel density estimation (KDE) is a common non-parametric estimation method for measuring the probability density function of variables [53]. KDE, which is regarded for its prevalence in the realm of spatiotemporal research, serves as a key technique for analyzing and comparing the attributes of various locations, such as destinations and their corresponding times. It examines the distribution of destinations in neighborhoods and allows investigators to see where destinations are densely distributed and where they are more intensely dispersed. Even within individual sites, KDE can be used to determine activity areas or feature cluster analysis. Previous studies have shown that it has good applicability for analyzing user online behaviors and hotspot maps [54],

[55], check-in behavior [56], urban boundary definitions [57], and point-of-interest recommendations [58]. The calculation is given by Equation 2:

$$F\left(x\right)=\frac{1}{nh^{d}}\sum\nolimits_{i=1}^{n}K\left[\frac{\left(x-x_{i}\right)}{h}\right] \tag{2}$$

F(x) is the estimated density value at location x; K[ ] is the kernel function; h is the bandwidth; n is equal to the total number of features within the bandwidth; d is the dimension of the data; and $(x-x_{\mathrm{i}})$ is the distance between feature x_{i} and location x [59].

2) GEOGRAPHICALLY WEIGHTED REGRESSION

To understand the driving factors of the distribution of popular attraction sites, our study proposes a geographically weighted regression (GWR) method and OLS to explore the influencing factors (Table 1) and the evolution mechanism [60]. More importantly, the spatial nonstationarity of relationships, for example, how the regression parameters change across different districts. GWR extends OLS regression by estimating local parameters rather than unique global parameters for the entire study area [61]. The GWR model was able to better explain local variations in impact and reduce the spatial autocorrelation of model residuals [62]. GWR estimates as many coefficients as there are local areas, thus better reflecting the spatially varying relationships between the dependent and explanatory variables. Furthermore, we used three criteria to select a suitable regression model [63]. (1) The adjusted R-squared should be equal to or greater than 0.5 ($R^2 > 0.5$), which denotes the goodness of fit of the model. (2) Significantly correlated factors (p-value less than 0.05) were selected as explanatory variables for the distribution of city image hotspots. (3) The value of the variance inflation factor (VIF) of the explanatory variables should not exceed 7.5 (VIF < 7.5), which ensures that there is no multicollinearity or redundant independent variables in the regression mode.

III. RESULTS

A. CHARACTERISTICS OF CITY IMAGE HOTSPOTS

1) SPATIAL DISTRIBUTION OF CITY IMAGE HOTSPOTS

The city image hotspots are concentrated in the central urban area. Specifically, the hotspots are distributed in the old urban areas inside the range of the Ming City Wall, with Confucius Temple as the center, and are scattered outward in a circular pattern. There are some hotspots scattered around suburban areas, such as the Niushou and Qixia Mountains. The hotspots of the outer suburbs are located primarily in the Lishui, Gaochun, and Luhe districts (Figure 5).

The data obtained ‘‘check-in’’ are classified according to similar locations, and the number of users in the same city image hotspot space is counted and sorted. Confucius Temple (夫子庙), Xuanwu Lake (玄武湖), Laomen East (老门东), Jiming Temple (鸡鸣寺), Nanjing Museum (南京博物馆), Xinjiekou (新街口), Qinhuai River (秦淮河), Sun Yat-sen's Mausoleum (中山陵), Ming Xiaoling Mausoleum (明孝陵), Niushou Mountain (牛首山), Nanjing Presidential Palace (总统府), Yihe Road (颐和路), Pioneer Bookstore (先锋书店), Hongshan Forest Zoo (红山动物园), Music Stage (音乐台), Meiling Palace (美龄宫), Ke Lane (科巷), Linggu Temple (灵谷寺), Wutong Avenue (梧桐大道) and Porcelain Tower of Nanjing (大报恩寺) are the hotspots in the top 20. The numbers of the top 20 ‘‘check-in’’ locations represent 61.3% of the total, with Confucius Temple having the highest percentage.

TABLE 1. Units for magnetic properties.

Dimensions	Variables	Description
Functional perception	Functional mixing degree	Shannon Diversity index
	Nighttime light	Nighttime Lights
Traffic perception	MED 1000 m	Closeness of search radii 1000 m
	MED 3200 m	Closeness of search radii 3200 m
	MED 6000 m	Closeness of search radii 6000 m
	MED 8500 m	Closeness of search radii 8500 m
	BTE 1000 m	Betweenness Euclidean of search radii 1000 m
	BTE 3200 m	Betweenness Euclidean of search radii 3200 m
	BTE 6000 m	Betweenness Euclidean of search radii 6000 m
	BTE 8500 m	Betweenness Euclidean of search radii 8500 m
Emotion perception	Positive emotion perception	Proportion of positive emotions
	Negative emotion perception	Proportion of negative emotions
Visual perception	SVF	Sky view factor
	Street greenery	/
	Color complexity	/

With respect to the distribution area, the Xuanwu, Qinhuai, Gulou, Jianye, and Jiangning districts are the main jurisdictions, which essentially encompass the central region of the main city. The largest number of hotspots is found in Xuanwu District, and 13 of the top 20 hotspots are also located in this district.

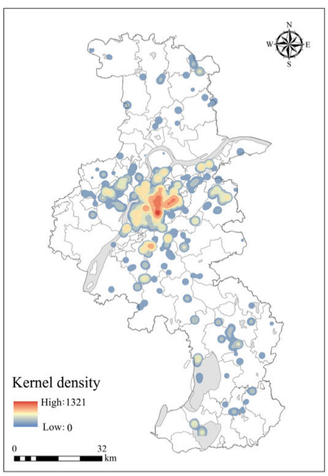


FIGURE 5. Distribution of city image hotspots in Nanjing.

2) TYPES AND STRUCTURES OF CITY IMAGE HOT SPOTS

We divided city images into 10 types: walking roads, public cultural facilities, green space parks, traffic nodes, scientific and education, commercial entertainment, special buildings, rural landscapes, heritage sites, and natural landscapes. Its proportion is mainly heritage monuments, accounting for 42.9%, with the Xuanwu and Qinhuai districts having the most obvious distribution. In addition to 15% of the park's green space and 13.4% of its public cultural facilities, the former is distributed in the central urban area, and the latter is distributed in the old city. Pedestrian roads and commercial entertainment accounted for 9.4% and 8.1%, respectively, and were concentrated in the Gulou, Xuanwu, and Qinhuai districts. The proportions of scientific and education, traffic nodes, and rural landscapes are similar, all of which are 1.5%. The rural landscape is concentrated in the Jiangning suburban district, which is related to the continuous implementation of the ''Beautiful Village'' reconstruction project.

TABLE 2. 10 types of city images and their respective proportions.

city images type	proportions
heritage monuments	42.963%
green space parks	14.953%
public cultural facilities	13.748%
pedestrian roads	9.499%
commercial entertainment	8.175%
natural landscapes	5.581%
scientific and education	1.579%
traffic nodes	1.549%
rural landscape	1.428%
special buildings	0.792%

B. PERCEIVED CHARACTERISTICS OF CITY IMAGE HOTSPOTS

1) PERCEPTION OF THE DEGREE OF MIXING OF FUNCTIONAL AREAS

To study the degree of mixing among functional areas, we divided the study area into regular grids with the same distance (the grid size was set to 1000 m). For each spatial unit, there is one or more POIs, and the function of the POI determines the spatial unit's function. SHIDI values were calculated for all spatial units to identify the degree of mixing of mixed functional areas. There are 3065 mixed functional areas and 23 types in the central urban area (Figure 6). The maximum value of the degree of functional mixing was 3.98, and the areas with medium and high degrees of mixing were distributed in the central downtown area (most attractions in the Gulou, Xuanwu, Qinhuai, and Yuhua districts), with small numbers distributed on Jiangpu Street, Yanjiang Street (Pukou District), Luhe District and Nanjing Economic Development Zone. The medium- and high-degree mixing areas cover a total of 584.11 km^2, which represents 55.02% of the area. The centers of the Pukou and Qixia districts and Xigang Street (Jiangning district) are characterized by a low degree of overall mixing, inadequate comprehensive urban development, and inefficient land use. In general, the central urban area is more concentrated, whereas the periphery is less scattered. The development of the old city is relatively mature, the degree of land mixing is high, the overall degree of functional mixing outside the old city is low, and there is still a gap between the comprehensive and multifunctional urban environments. Overall, the distribution of functional perceptions in the central urban area is not uniform, with a high value in the old city and a low value in the Jiangbei development zone. The area with a high value of functional perception is also the central part, with a comprehensive infrastructure, frequent human activity, a high consumption level, and a large agglomeration of facilities, such as food, accommodations, travel, tourism, shopping, and entertainment. On the other hand, the old city has a long history, preserving traditional patterns of functional mix. Over time, these areas have accumulated diverse land use and building types, resulting in areas with high functional perceptions. Compared with the old city, the high-value area in the Jiangbei development zone has more farmland and technology parks, a lower population, fewer POI types, and a lower travel demand, resulting in a low degree of mixing in the urban land use function. Urban land with a single type of use forms low value areas, which also indicates that the infrastructure of this land needs to be improved.

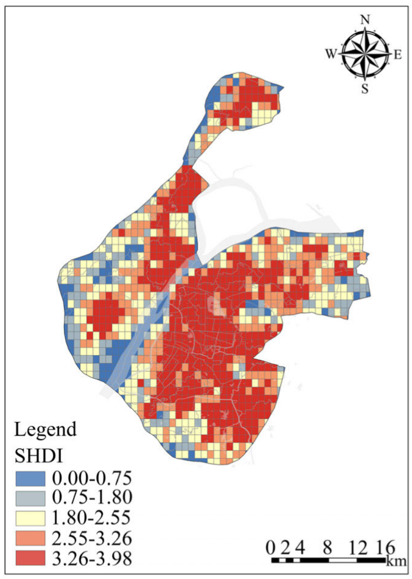


FIGURE 6. Distribution of functional perceptions in the central urban area of Nanjing.

2) PERCEPTION OF THE URBAN TRAFFIC SITUATION

Four distinct travel modes were simulated, and their closeness and betweenness under different search radii were examined: walking (search radius of 1000 m), using public transportation (search radius of 3200 m), riding a subway (search radius of 6000 m), and driving a private vehicle (search radius of 8500 m). For radii less than 1000 m, the degree of closeness by walking in most spaces is low, with yellow and blue colors. Only Qixia Ancient Town, Nanjing Garden Expo Park, and Green Water Bay Park have high closeness (Fig. 7A). These areas, which are all meticulously planned by Nanjing, are green and leisure spaces. They are surrounded by numerous parks and cultural hubs, such as the Youth Olympic Park and Tangshan Park. The distance between these sites is relatively close within the walking search radius.

Under this range of activities, the betweenness of the Xinjiekou and Nanjing South Railway Stations is high, as shown in red, and the betweenness of other image hotspots is low, as shown in blue (Fig. 7E). Xinjiekou is the commercial center and serves as a traversed location within the urban landscape. Nanjing South Station serves as an integrated transportation hub for trains, subways, and buses, connecting various functional areas, and thus becomes a transfer point on walking routes. The bus is the most active transport mode when the activity range is greater than 3200 m. The closeness of most of the city image spaces in the old city has improved, but the closeness of Hongwu Road is still low (Fig. 7B). Owing to its location in the old city, the surrounding residential area is densely populated with more than 30 neighborhoods. There are many sidewalks and relatively few main arterials for public transportation, resulting in limited public transportation coverage and thus low closeness between locations within these areas. Furthermore, the industrial area at the edge of the city is mainly a low-closeness area, such as Xishan Bridge Street, Banqiao Bridge Street, and the Nanjing Economic Development Zone. Limited public transportation coverage results in potentially lower closeness. The high betweenness space is concentrated in Xinjiekou, Nanjing South Station, and Hexi New Town, forming an extension along the Central Road as the longitudinal axis within the old city (Fig. 7F).

For radii less than 6000 m, the closeness of the spatial distribution is nonuniformly distributed, reflecting the spatial layout characteristics of low-core and high-edge areas. The spatial range of high betweenness is further expanded (Fig. 7G). Despite its long mileage, Nanjing Metro serves mainly suburbs. There are only four subway lines in the core area, and the number of metro stations is low. Areas with higher betweenness are metro transfer stations or commercial hubs, such as Xinjiekou, Nanjing South Station, Gulou, and Daxing Palace. In contrast, there are fewer suburban transfer stations and commercial centers, as exemplified by the Xianlin and Jiangning University areas. These locations may not be major transit points within the metro network; hence, their betweenness values are lower.

For radii less than 8500 m, people's activities rely on long-distance transportation, such as private cars. High-closeness areas are concentrated in residential-oriented areas around the central area, such as Qilin, Jiangxinzhou, north of the Yangtze River Bridge in Pukou district, and Maigaoqiao. Private vehicles can quickly navigate various residential streets, contributing to greater closeness. Furthermore, the closeness of the space along the river also improved (Fig. 7D). Areas such as Xianlin and Hexi are home to numerous suburban shopping centers and large malls. These regions typically offer an abundance of parking spaces and enjoy convenient road connections, making private vehicle mobility more convenient. Although the high betweenness areas do not vary compared with the radii of 6000 m (metro radius), they possess a higher betweenness because the urban external orbital and major junctions are crucial routes and connection points for private car travel (Fig. 7H).

3) PERCEPTION OF RESIDENT EMOTIONS

The algorithm has a good recall ratio (0.92) and precision degree (0.90) for the recognition of positive perception; the recall ratio and precision degree of negative emotions are 0.81 and 0.85, respectively. We selected sites with more than 10 comments on the check-in data, and the emotion map was drawn with ArcGIS 10.8.2. The spatial distribution of the "check-in" hotspots is shown in Figure 8. We subsequently standardized the emotional scores of different check-in sites and reclassified the score results into five categories according to Jiang et al. [64]. The scores (0.49-0.57) were median values, which are indicative of a neutral emotion. Scores greater than 0.57 were designated as reflecting positive emotions, whereas values less than 0.49 were characterized as negative emotions. In general, the average emotion value in the central urban area was above 0.57, which was considered a high emotional area. The highly emotional areas are located in heritage monuments, commercial entertainment, and green space parks. These spaces have a long history, a variety of delicious snacks, a warm and cheerful atmosphere, and a rich natural environment. Examples include Xuanwu Lake (0.572), Jiming Temple (0.589), Confucius Temple (0.587), and Linggu Temple (0.581). Furthermore, the average value of low emotion areas was less than 0.49 according to Jiang et al. [64]. The negative emotion areas, such as the Sun Yat-sen Mausoleum (0.245), the tomb of Li Wenzhong (0.402) and the National Innovation Park (0.213), are distributed in tomb parks with a solemn atmosphere and mountains in suburban areas that have low-intensity construction, inadequate infrastructure, public service facilities, and high commodity prices.

According to the main areas of concern in urban planning and spatial governance, a corpus of emotional factors was constructed according to Ma et al. [16]. The results revealed that the top 10 factors causing positive emotions were "mountain", "garden", "lake", "delicious food", "museum", "bookstore", "park", "sunset", "music", and "temple". Additionally, "nuisance", "overcrowding", "debris", "heavy rainfall", "expensive", "garbage", "disorderly", "noise", "invisible consumption", "storm", and "heat" were the top 10 factors associated with perceiving negative emotions. Most negative emotions arise from the following issues: (1) Some areas are noisy. Road traffic and construction noise are tied to "annoying" and "noisy", such as the Maigao Bridge street; (2) some tickets are excessively high, while viewing experiences and services do not deserve such expensive tickets; (3) visitors suffer from excessive flows of people at peak times, together with severe congestion and endless queueing times, which adversely affect

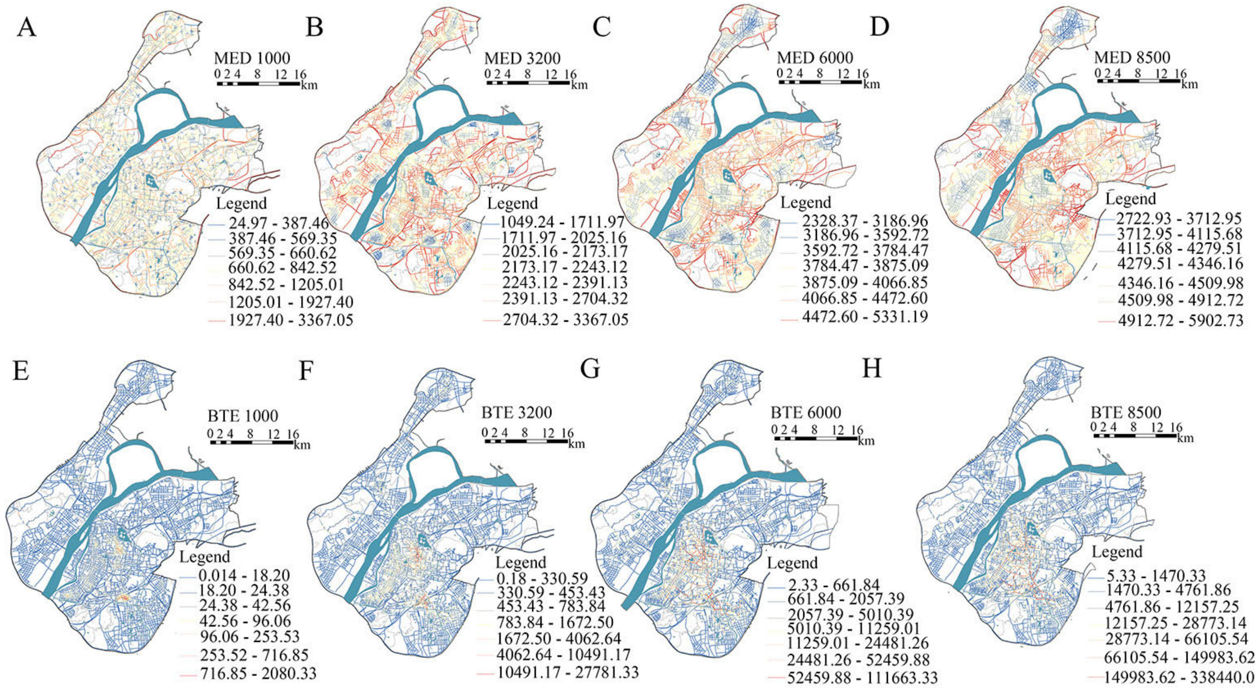


FIGURE 7. Distribution of functional perceptions in the central urban area of Nanjing.

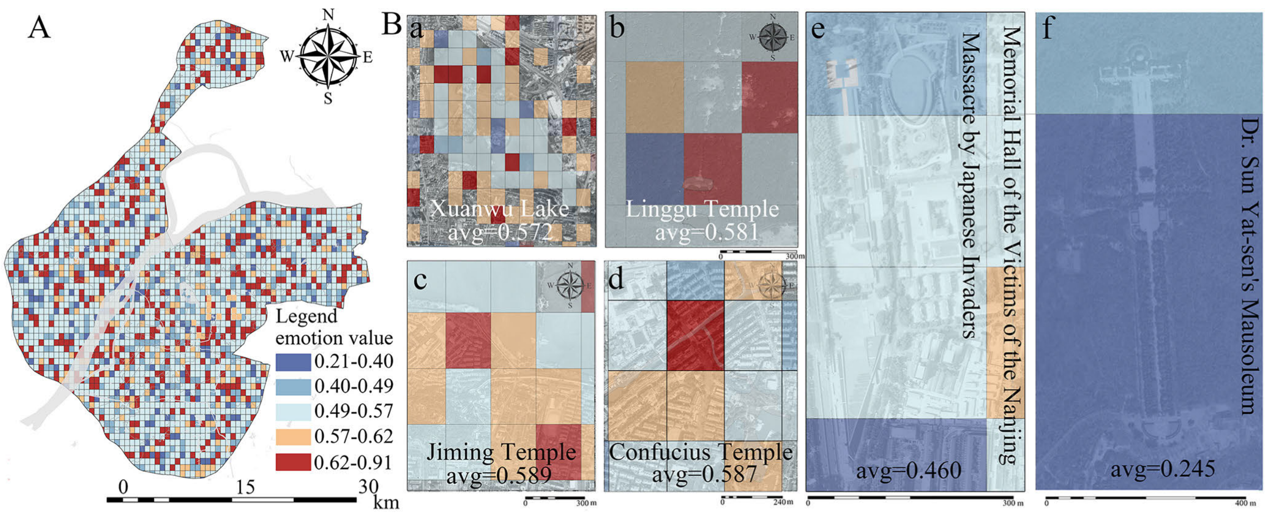


FIGURE 8. Distribution of emotional perception in the central urban area of Nanjing.

travel experiences to a large extent; and (4) bad weather and the environment affect travel experience. Furthermore, the words ''mountain'', ''lake'', ''sunset'', ''heavy rainfall'', and ''storm'' could be considered synonymous with the natural environment, suggesting that the quality of the environment was the most ardent demand of residents. ''Music'', ''nuisance'', and ''noise'' indicate that the soundscape is the key factor affecting the perception of emotions. ''Delicious food'', ''Duck blood vermicelli soup'', ''coffee'', and ''soup dumplings'' were synonyms for the ideal life of leisure and elegance with Nanjing characteristics; these words were distributed in the central area centered on Xinjiekou. The term ''disorderly'' represented the disorderly space, appearing mainly in the residential area of the old city, indicating that the bustle space needs more governance.

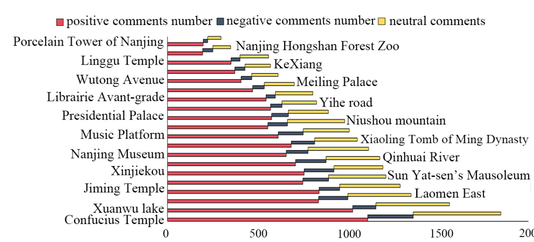


FIGURE 9. Emotional perception in the top 20 hotspots.

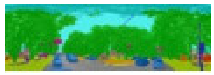
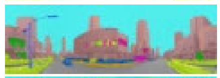
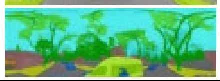
FIGURE 10. The word cloud of emotional perception in the central urban area of Nanjing. A. Elements induced positive emotions B. Elements induced negative emotions.

4) PERCEPTION OF VISUAL

Part of a CSV file is given in Table 2, which shows some of the segmentation results for six sampling points. The ranking in the top 20 hotspot sky view values is in the range of 0.47-0.66, suggesting a moderate degree of openness with partial obstructions present. This phenomenon can be attributed to the high-density urban fabric, where the proliferation of buildings restricts skyward visibility. Furthermore, the value of visible greenery in the streetscape is 0.242-0.931. Aoki noted that most people have a favorable impression of a street landscape when the value of visible streetscape greenery is at least 0.3 [65]. Our findings revealed that 60% of the top 20 hotspots presented a visible greenery value greater than 0.3, mainly in Confucius Temple, Xuanwu Lake, Ming Xiaoling Mausoleum, Nanjing Museum, Sun Yat-sen Mausoleum, Linggu Temple, Meiling Palace, Niushou Mountain, Ming city wall, Wutong Avenue, Hongshan Forest Zoo, and Yihe Road. Most of these areas are important historical sites or monuments (such as the Ming Xiaoling Mausoleum, the Sun Yat-sen Mausoleum, and the Meiling Palace) that rely on mountains to be built with earlier vegetation planting. Wutong Avenue and Yihe Road were included in greenway planning in 1929. The surrounding area of the sites was also subject to careful preservation, with a particular focus on the maintenance of greenery. Some of these areas are parks or natural landscapes, such as Xuanwu Lake, Niushou Mountain, and Nanjing Hongshan Forest Zoo. These areas are typically characterized by a high density of arboreal, herbaceous, and grassland vegetation. However, among the 20 hotspots identified, East Zhonghua Gate, Jiming Temple, and Porcelain Tower were also heritage monuments but presented low visible greenery value. This may be related to the fact that they are located in downtown areas and have more human activities, so it is recommended that arboreal and shrub species be strategically planted along the streets and that climbing flora be integrated into the vertical surfaces of the buildings.

In addition, we extract the streetscape color of the check-in spots on the basis of streetscape images and the color features of the streetscape via machine learning algorithms. The color complexity values of the six different types of intervals are 20.68, 11.28, 29.31, 14.83, 18.45, and 8.81. The color complexity values of the other top 20 hot spots are mostly approximately 19.64-27.89.

TABLE 3. Visual perception of different hotspot types in the urban center area of Nanjing (partial data).

name	Semantic segmentation results	Street greenery	SVF	Color complexity
Confucius Temple		0.3129	0.3666	20.680
Xuanwu lake		0.4752	0.3474	11.287
Niushou Mountain		0.1986	0.6197	29.312
Nanjing Museum		0.5883	0.2210	14.839
Xinjiekou		0.0768	0.3971	18.450
Yihe Road		0.3261	0.3857	8.806

C. INFLUENCING FACTORS OF CITY IMAGE PERCEPTION

Various factors influence the spatial heterogeneity of check-in hotspots. Several factors were selected to explore the effects of perceptions on the spatial patterns of the hotspots. To address the collinearity between the independent variables, we calculated the correlations via OLS (Table 4), and all the factors passed the covariance test (VIF < 7.5), except for BTE 3200 (VIF = 17.3), BTE 6000 (VIF = 44.1) and BTE 8500 (VIF = 20.3). The P value of all factors was also less than 0.05 except for light (p = 0.20) and MED 1000 (p = 0.53).

After a comprehensive analysis, a total of 9 independent variables (MED 3200, MED 6000, MED 8500, sky view factor, emotion value, streetscape greenery, streetscape color, SHDI, and BTE 1000) were selected for modeling the geographically weighted spatial pattern driving factors of hotspots (GWRs). The results obtained via GWR were characterized by higher R^2 (0.538) and lower AICc (6113.96) values than those of the corresponding OLS models (R^2 = 0.378, AICc = 6830.59). The distribution of popular attraction sites was associated with perceptions.

Furthermore, Table 4 indicates that MED 6000 and MED 8500 were the dominant factors that contributed to the spatial heterogeneity in the hotspots. The SHDI and SVF had relatively greater impacts on popular attraction. In contrast, a single influencing factor, streetscape greenery or emotion value, exhibited relatively weak explanatory power with respect to spatial disparities in popular attraction.

As shown in Fig. 11, the relationships between the variations in the nine perception values and the popular attraction index varied spatially. The driving forces of the perception of popular attraction sites changed with the variation in spatial

TABLE 4. The results of the ordinary least squares.

variable	coefficient	standard deviation	t	probability	VIF (c)
MED 3200	0.125	0.0229	5.471	0.00*	2.43
MED 6000	-0.608	0.0349	-17.439	0.00*	5.65
MED 8500	0.538	0.0334	16.123	0.00*	5.19
Emotion value	0.036	0.0151	2.390	0.02*	1.06
sky view factor	0.224	0.0178	12.603	0.00*	1.47
streetscape greenery	-0.042	0.0182	-2.312	0.00*	1.55
streetscape color	-0.112	0.0153	-7.323	0.00*	1.08
SHDI	0.469	0.0202	23.169	0.00*	1.90
BTE 1000	0.194	0.0229	6.481	0.00*	4.16

position. The same factor may have different magnitudes of impact at different locations. MED 8500, MED 6000, BTE 1000, sky view factor, streetscape greenery, streetscape color, emotion value, and functional mixing degree were found to have negative or positive impacts on popular attraction in various areas.

For MED 8500, a strong positive effect was observed in the Qinhuai district (East Zhonghua Gate Historical Culture Block, Qinhuai River, Bailuzhou Garden, and Zhanyuan) and a negative influence was identified in the suburbs (Taifeng Lu, Getang, and Qixia ancient towns).

MED 6000 was found to be negatively related to the hotspot distribution in the city (especially in the rainflower terrace and Dengyumu in the Yuhuatai district). A positive effect of the MED 6000 was observed in the Pukou and Luhe districts. The degree of functional mixing and the sky view factor positively contribute to popular attraction, with the most obvious contribution occurring in the central urban area. That is, the higher the degree of functional mixing and the SVF are in these areas, the greater the number of attendance. The regression coefficient of the influence of streetscape greenery on the hotspot distribution was 53% in the positive region, which is located in most attractions in the Gulou, Qinhuai, Jianye, and Yuhuatai districts. The rest of the central urban area presented negative values.

Street scene color had negative effects on most of the central urban areas. Streetscape color had a more significant negative impact on popular attractions in the Jianye district (such as Nanjing China Green Expo Garden and Nanjing Constitution Park), the Pukou district (Phoenix Mountain, Xiangshan Park, and Lanxi Park), the Qixia district (Qixia Ancient Town and Xianlin Lake Park) and the Luhe district (Zhimaling Park).

The emotion perception factor, as an important indicator reflecting emotions, also influences the spatial divergence of the check-in number to some extent. In general, emotional value has a positive effect on the number of check-ins. The positive effect of emotional value on check-in numbers is most evident in the southern Xuanwu and Qinhuai districts. A positive correlation was identified between the MED 3200 and the check-in number, indicating that as the closeness (not exceeding 3200 m) increases, the attraction of the population also increases. BTE 1000 was found to be positively related to the number of check-ins in the suburbs, and a negative effect of BTE 1000 was observed in the central urban area.

IV. DISCUSSION

A. RELIABILITY AND LIMITATIONS OF CITY IMAGE PERCEPTION RESULTS BASED ON BIG DATA

First, newly emerged check-in data provide much richer and more detailed temporal and spatial information than traditional data sources do [27]. Our study uses geotagged data from 205,091 users of the "Little Red Book" and "Weibo" in Nanjing, which are difficult to collect via traditional approaches. Geotagged social media data with messages and check-ins are better for understanding the subjective and spatial dimensions of city images than mobile positioning data are [66]. The accessibility of social media in real time allows individuals to immediately perceive their actual thoughts, feelings, and behavioral preferences.

Second, using a large number of real open feelings after traveling as basic data has the advantages of wide data samples, highly objective evaluation truth, and a more comprehensive perspective, which can accurately quantify the attractiveness of the target area. The findings of the TF-IDF analysis reveal public actions and focus points. For example, the yellow crane tower is the most widely used city image vocabulary in Wuhan. These are the landmarks of local cities. Like in previous studies [67], Confucius Temple (4123) is the most common city image vocabulary in Nanjing and a cultural card for the renewal of the ancient city. "Historical monuments" have various high-frequency features, reflecting strong environmental experience. This coincides with Nanjing having a history of 6,000 years of civilization and an urban history of 2,500 years [68]. It also matches the perceptions of overseas students of Nanjing as "a lengthy history", "culture", and "Nanjing is a world-famous historical capital" [69]. Our investigation revealed that numerous comments referenced "nice", "recommended", and "convenient", indicating positive emotions. Some remarks mentioned "repress", "just so", and "crowd", which meant unpleasant emotions. Overall, the public perception of Nanjing's image is positive, which is consistent with previous results [70].

Third, through in-depth analysis of city image characteristics extracted from social media information data, city image research can shift from subjectively "guiding research" to objectively "noninterventional research" and suggest the optimization of city image hotspots on the basis of perceptual data. The "natural landscape" in the city image hotspots represented a small proportion, and the traditional landscape city image gradually blurred, whereas previous studies have shown that the beautiful landscape and historic buildings can easily arouse the emotional experience of tourists. With

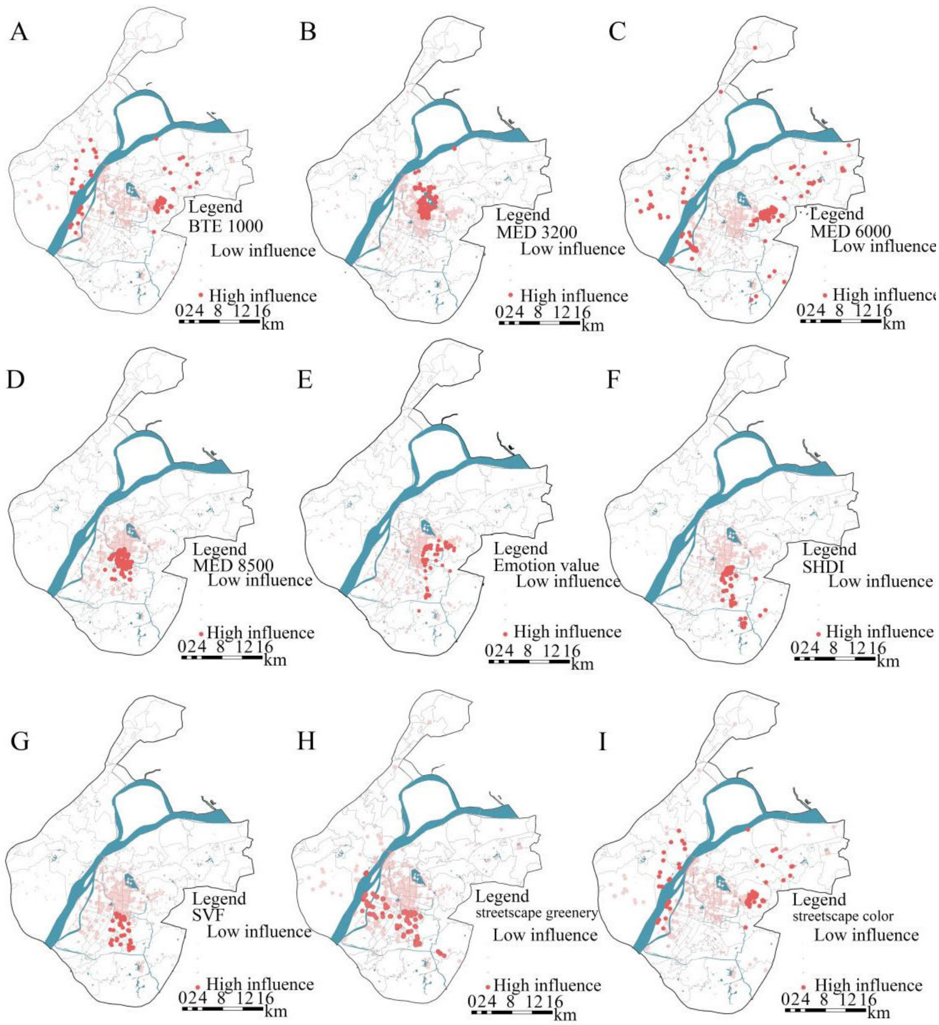


FIGURE 11. **Spatial pattern of the correlation coefficients between check-in hot spots and indicators of public perception Note. A. BTE1000m; B. MED3200m, C. MED6000m, D. MED8500m; E. emotion perception value; F. SHDI; G. SVF; H. streetscape greenery; I. streetscape color.**

respect to the emotion theme [71], the landscape is the first element that triggers travel emotion [70]. This means that we should strengthen the construction of the landscape environment in Nanjing. For spaces with high satisfaction but low identifiability, we should comprehensively study the elements of the image that attract people in these regions, create more elements of the perception of demands, strengthen public relations, and improve the image of the above spaces. For areas with high identification and attention but relatively low satisfaction, such as Ke Lane and Suojin Village, ''have no'', ''expensive'', and ''disappointed'' indicate that actual perceptions are different from expected expectations; these areas should be targeted to improve management.

Our study confirms the feasibility of using social media data to analyze the public perceptions of city images. The method covers a wide range of subjects with high authenticity and analyzes city images more deeply, encompassing both material and immaterial environmental elements. It identifies elements neglected in traditional studies and offers a novel perspective for understanding urban space and improving urban quality. However, our study also has certain limitations. First, owing to the age limitation of social media users, 72% of users are between 18 and 34 years old, which can lead to the neglect of the perceptions of the elderly and underage children. Second, human perceptions are also affected by subjective factors such as past experiences, level of education, and family culture [72]. Our study can be further enriched by combining questionnaires and other microdata in the future.

B. THE CORRELATION BETWEEN CITY IMAGE PERCEPTION AND HOTSPOTS

Our study indicated that subjective perceptions and the objective environment affect city image hotspots. Functional perception, traffic perception, emotional perception, and visual perception all have an impact on the hotspots of city images. The city image has subjective and objective aspects [24] from an empirical point of view. Subjective emotional perception and the objective environment are interconnected. Previous studies have shown that recreational use, tourism infrastructure, and safety can interfere with the perception of major environmental factors. Furthermore, environmental perceptions can be strongly influenced by the culture of the landscape environment [73], local social and economic conditions [74], and information from the media. For example, the objective view indices of the sky, roads, sidewalks, people, cars, walls, railings, and water have been shown to be positively correlated with running amount in studies of outdoor runners' behavior [75]. The commercial atmosphere, plant landscape, accessibility of the road space, architecture, and surrounding environment affect the heat value of the tourist flow. In addition, Qiu et al. [76] reported that visual perception plays an important role in the user experience of the urban landscape and could affect the level of use of public space. We have also verified that visual perception (streetscape greenery, the sky view factor, and streetscape color) can affect city image hotspots and can drive emotional perception. Functional perception (functional mixing degree and night light) and traffic perception can drive emotional perception and affect the identifiability of city image hotspots together with emotional perception. Among them, functional perception and traffic perception have a stronger influence. The degree of opening and service scope of functional classes can determine the one-time contact of the public with the image nodes, which affects whether the image points make an impression on the public. Functional categories of life can determine the multiple interactions of the public with image points, affecting whether the impression becomes increasingly profound. The public perception of space has spatial accessibility and perceived accessibility, and interventions in spatial cognition can have a more significant impact on people's behavior than can interventions in the objective environment [77]. An increase in greenery on streets can promote positive emotions in people, which is consistent with the results of previous studies [78]. The Gulou, Xuanwu, and Qinhuai districts in the central urban area had high functional mixing, complete facilities and services, and high betweenness but low streetscape greenery. In future urban construction, we can focus on these factors on the basis of geographical sampling and improve landscapes in tourist-unfriendly areas.

V. CONCLUSION

Our study enriches the research on city image from an empirical perspective. We constructed a city image perception model ($R^2 = 0.533$) through the notes "Nanjing check-in data" from "Little Red Book" and "Sina Weibo" and obtained a more accurate and ideal regression model. The hotspot spaces of the city image show obvious aggregation characteristics and are distributed mainly in the central urban area. The types are mostly heritage monuments and less rural landscapes. The emotional expression of the hotspot spaces is more positive, and positive emotions are gathered in the city center, with a contiguous tendency. Objective factors such as nighttime light, accessibility to traffic, the sky view factor, street greenery, and the degree of functional mixing affect emotional perception. Emotional, visual, traffic, and emotional perceptions all affect city image hotspots, and functional and traffic perceptions are more influential.

Our study provides the following references for Nanjing urban planning. First, the urban imagery of the natural landscape should be strengthened. Since ancient times, Nanjing has been famous for its natural landscape. However, the proportion of natural landscapes in the hotspot imagery space is relatively low (only 5.58%). In addition, emotional pleasantness was significantly correlated with spatial variation in green visualizations. Therefore, Nanjing's green urban imagery needs to be further highlighted. Second, the completeness and accessibility of the spatial structure of urban imagery should be improved. The construction of basic functional facilities in the Jiangbei region should be accelerated to narrow the gap with Jiangnan. Strategies should be formulated from the perspectives of hotspot spatial optimization and functional replacement to alleviate the problems of the uneven distribution of traffic perception and the overburdening of traffic in the old city. Third, we should focus on the inheritance of traditional culture. The elements that can stimulate positive emotions are concentrated in "food", "mountains", "lakes", and "museums". The humanistic festival elements that represent cultural charm are seldom mentioned. Therefore, it is recommended that public space be used to organize various cultural activities and festivals to enhance a city's cultural characteristics.

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