Exploring the Emotional Spatial Patterns and Functional Perceptions of Internet-Famous Streets Based on Large Language Models: A Case Study of Nanjing Old City

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Abstract
This study analyzes over one million geo-tagged Sina Weibo posts (2019–2024) to evaluate emotional patterns and influencing factors on internet-famous streets in Nanjing Old City. First, high-traffic streets and their functional zones are identified using ArcGIS-based spatial analysis. Second, advanced large language models (LLMs) are used to detect residents' and tourists' emotions through a four-dimensional structure: primary and secondary emotions, intensity, and polarity. These emotional labels are mapped to street-level sentiment profiles. Spatial clustering and semantic analysis reveal distinct emotional dynamics driven by spzeatial semantics and functional typologies.

Keywords: large language model; internet-famous streets; social media sentiment; urban emotion map; Nanjing old city

1 Introduction

With the rapid development of information and communication technologies, society has quietly entered the era of big data. The widespread use of GPS, mobile devices, and the internet has brought new opportunities for urban spatial perception research. Since 2012, disciplines such as urban geography, planning, and sociology have increasingly embraced big data, with location-based social media becoming a prominent data source. Check-ins are considered conscious behaviors—users tend to post only when they spend significant time in a location worth recording, reflecting their emotional and psychological states (Yadollahi, A., 2017).

Against this backdrop, geo-tagged data from social media enables researchers to capture spatial emotional interactions and geographic tendencies. It has been widely applied in urban zoning, spatial evaluation, vitality analysis, and spatiotemporal behavior studies. Sina Weibo, as one of China's most popular social media platforms, offers broad national coverage and robust user-generated data for such analyses.

Meanwhile, networked communication has reshaped social and spatial experiences. The rise of online interaction has increasingly influenced physical urban space—cloud experiences often replace physical ones, and media representation tends to precede actual function. As a result, media-oriented "internet-famous streets" have proliferated (Niu, X. and Lin, S., 2022). Streets, as key urban spaces for communication and culture, now serve as dynamic platforms for emotional expression and interaction among users.

However, traditional sentiment analysis methods based on rule-based or shallow classifiers struggle with unstructured, ambiguous, or sarcastic content common in social media texts (Nandwani, P. and Verma, R., 2021). With the advent of large language models (LLMs), such as ChatGPT, sentiment analysis has entered a new phase. Trained on vast corpora, LLMs can understand context, capture nuanced emotions, and infer user attitudes and motivations (Lü J., 2022.), significantly enhancing the accuracy and interpretability of emotional computing.

In the field of emotion research, scholars have developed relatively mature theoretical frameworks across various dimensions. Emotion dimension theories propose that emotions can be understood through multiple attributes, with two- and three-dimensional models being the most widely used. Russell introduced the two-dimensional model, suggesting that emotions can be interpreted along two axes: valence (positive to negative) and arousal (high to low intensity) (Russell, J.A., 1980.). Valence reflects pleasantness, while arousal captures emotional intensity or excitement. Later, Mehrabian and Russell (1994) proposed the PAD model (Mehrabian, A., 1980.), a three-dimensional theory consisting of Pleasure, Arousal, and Dominance. In this model: Pleasure (P) represents the positive or negative quality of the emotion; Arousal (A) indicates the level of emotional activation or excitement; Dominance (D) reflects the degree of control or influence the individual feels within a given environment. In terms of classification, psychological theories typically distinguish between basic and complex emotions. However, definitions of basic emotions vary significantly among researchers due to differing perspectives from linguistics, behavioral science, and other fields. Figure 1 below outlines several mainstream classification systems and their respective emotional categories.

Researcher	Categories	Specific Emotions
Darwin	6 types	Joy, Sadness, Anger, Fear, Disgust, Surprise
Arnold	11 types	Sadness, Anger, Terror, Disgust, Anticipation, Hope, Frustration, Disappointment, Expectation, Resentment, Love
Izard	10 types	Joy, Sadness, Anger, Fear, Disgust, Surprise, Interest, Shame, Guilt, Contempt
Ekman	6 types	Joy, Sadness, Anger, Fear, Disgust, Surprise
Johnson	5 types	Joy, Sadness, Anger, Fear, Disgust
Lazarus	10 types	Joy, Sadness, Anger, Fear, Disgust, Jealousy, Pride, Shame, Love, Comfort

Figure 1: Basic Emotion Classifications (Image source: redrawn based on Reference 6)

In the domain of spatial emotion research, scholars began exploring the relationship between space and emotion as early as the mid-20th century, proposing concepts such as “place perception” and “place attachment” to examine how spatial environments influence human emotions. Initial studies emerged in philosophy, sociology, and psychology before expanding into specific investigations on how spatial elements trigger emotional responses and the types of emotions involved. These studies often adopt macro, meso, or micro-scale perspectives to depict the spatiotemporal distribution of emotions and explore their associations with physical spatial elements.

At the macro scale, research focuses on citywide emotional distributions and their correlations with urban form and built environment. This stream typically employs big data analysis, especially from geo-tagged social media. Bertrand mapped emotional tendencies across New York City using Twitter data, finding that parks concentrated positive emotions, whereas facilities like transport hubs, cemeteries, hospitals, and prisons correlated with negative sentiment (Bertrand, K., Bialik, M. and Virdee, K., 2015.). Shanshan Chen et al. analyzed Twitter data from 26 parks in Berlin to examine how cultural demands and green space supply interact to affect public emotions (Chen, S., Liu, L., Chen, C. and Haase, D., 2022.). Sakshi Khare et al used Bhopal, a rapidly growing Indian metropolis, as a case study to explore the link between urban built environment and subjective well-being (Khare, S. and Chatterjee, A., 2023.).

At the meso and micro scales, studies often focus on streets, parks, squares, and neighborhoods, using data sources such as surveys, interviews, or physiological signals. Li et al. examined the emotional coupling between people and urban spaces to evaluate spatial environments and provide recommendations for improving urban design (Li, X., Hijazi, I., Koenig, R., et al., 2016.). Hijazi et al. combined Twitter sentiment data with spatial features to analyze how certain spaces or spatial sequences trigger emotional arousal (Hijazi, I.H., Koenig, R., Schneider, S., et al., 2016.). Similarly, Koenig et al. used one week of Twitter data from Osaka to show how pedestrian emotions shift with spatial sequences (Koenig, R., Schneider, S., Hamzi, I., et al., 2014.).

In the context of large language models (LLMs) and sentiment analysis, scholars have argued that "emotions have never been aliened in AI." LLMs have demonstrated promising potential in understanding social emotions. Traditional sentiment analysis methods—including dictionary-based approaches, machine learning, and deep learning—have been widely used. While dictionary-based methods match words with emotion tags, and machine/deep learning models can identify emotional types within specific contexts, they often struggle with complex emotional structures, mixed emotions, sarcasm, and contextual nuances. As a result, they risk misclassifying emotions in nuanced or ambiguous content (Maynard, D.G. and Greenwood, M.A., 2014.).

Recent advances in large language models (LLMs) have demonstrated exceptional performance in understanding human language. Fu highlighted the effectiveness of LLMs in analyzing public sentiment, emphasizing their ability to significantly reduce the time and cost associated with processing emotional corpora. Unlike traditional methods ((Fu, X., Sanchez, T.W., Li, C. and Reu Junqueira, J., 2024.), LLMs approximate human-like comprehension of complex emotional expressions. Li Yin applied ChatGPT to analyze multi-category and multi-level sentiments in COVID-19-related tweets across New York State, identifying nuanced emotional patterns such as relief, hope, and anxiety. The study achieved refined sentiment classification and thematic associations, revealing regional differences in emotional attitudes (Yin, L., Han, M. and Nie, X., 2024.). Gao M conducted sentiment analysis on geo-tagged social media data from 32 urban blue spaces in London using LLMs, introducing three indices—the Happiness Probability Index (HPI), Happiness Intensity Index (HII), and Happiness Equilibrium Index (HEI)—to quantify the impact of blue spaces on public well-being (Gao, M. and Fang, C., 2025.).

Building on existing sentiment analysis frameworks, this study utilises LLMs to analyze the spatiotemporal patterns of public emotion on internet-famous streets in Nanjing's old city. First, using preprocessed social media data and ArcGIS-based spatial analysis, high-traffic and high-engagement internet-famous streets are identified. Second, the functional tags of Weibo check-in locations are manually sorted, and classified into standardised categories: education, public services, parks and squares, transportation, commerce, residential, cultural and sports services, and others. Based on this, the dominant functional type of each street is determined. Finally, by applying a GPT-based LLM, the study extracts complex emotional structures from the dataset and conducts a street-level spatiotemporal analysis of emotion patterns in relation to spatial features and function types.

This research focuses on the following core questions:
(1) How can internet-famous streets be identified through virtual media, and how can their online popularity boundaries and physical boundaries be accurately delineated?
(2) How can the functional types of internet-famous streets be classified based on social media perspectives?
(3) How can LLMs be used to mine multi-level sentiment structures from Weibo texts, and what are the relationships between emotional spatial patterns and functional types on these streets?

2 Data and Methods

2.1 Data Source

Using "Nanjing" as the keyword, original Weibo posts containing check-in information for Nanjing from July 31, 2019 to July 31, 2024 were collected via a Python-based web scraping framework. After removing invalid entries—such as abnormal check-in records, advertisements, and blank posts—and cropping the dataset to the boundaries of Nanjing's central urban area, a total of 1,004,755 valid records were obtained.
Each valid entry contains the following fields: user nickname, province, check-in location name, check-in location

type, geographic coordinates (latitude and longitude), post time, and Weibo text. The check-in location type is a label provided by the Weibo API, which tends to be fragmented and thus required manual cleaning and classification.

This study focuses on internet-famous streets rather than the entire city or old town of Nanjing. Therefore, the text dataset is constructed at the street scale. Buffer zones were generated using a length of 150 meters—corresponding to pedestrian-scale street segments—around identified street linear features. All Weibo posts falling within these buffers were included in the final dataset of internet-famous streets, resulting in a total of 68,215 valid records.

nickname	province	Location name	Location type	latitude	longitude	post time	Weibo text
A roadside little flower kid	Other	Taiyanggong Square	Square	118.8089	32.06694	2024/7/31	To the one I may be separated from—salute giving up. ps: my crying voice is too ugly.
I want you to become a persimmon cake	Jiangsu	Baolong Times Plaza	Shopping mall	118.6333	32.05627	2024/7/31	The most relaxing moment after work every day. July comes to an end.
Big Bastard Pig	Jiangsu	Nanjing University of Aeronautics and Astronautics	University	118.8152	32.03713	2024/7/31	After the plum rain season comes the dog days—seamlessly connected.

Figure 2: Weibo Dataset Structure (Figure source: self-compiled)

2.2 Kernel Density Spatial Analysis

The principle of kernel density analysis is that each analyzed point is covered by a smooth surface, where the surface value is highest at the point's location and gradually decreases with distance until it reaches zero at the defined search radius. A larger search radius yields a smoother and more generalised raster surface, while a smaller radius results in steeper, more detailed raster outputs.

In this study, kernel density analysis is employed to identify the spatial clustering boundaries of point-based datasets, thereby delineating the virtual heat boundaries of hotspot check-in streets.

2.3 Multi-Level Sentiment Analysis Framework Based on Large Language Models

This study utilises OpenAI's pretrained generative transformer model (GPT) as the primary tool for multi-category and multi-level sentiment analysis. The model excels in text comprehension and generation, offering human-like interpretation of social media content and outperforming traditional natural language processing methods in semantic depth and accuracy. OpenAI's model has demonstrated excellent performance in multiple benchmark evaluations and is particularly effective for processing unstructured, noisy, and linguistically diverse data such as tweets. Compared to open-source large language models that often require complex GPU deployment, OpenAI's API offers greater accessibility and ease of use, enhancing both the efficiency and stability of this research.

Prior to emotion classification, we used the LLM to objectively extract the emotional tone of each tweet without preset category labels or emotional constraints. By analyzing the natural emotional expressions in a large corpus of raw texts, and based on commonly recognised emotion types in Chinese contexts, we identified frequent emotional categories within social media discourse. The model ultimately classified the following sentiment types:

• Positive emotions: anticipation, happiness, affection
• Negative emotions: sadness, disgust, anger
• Neutral emotions: neutrality

The model was instructed to identify both a primary sentiment and a secondary sentiment for each post. If a secondary sentiment could not be detected, it was left blank, but a primary sentiment was always required. Through prior prompt tuning, we also enabled the model to output both the sentiment intensity and polarity for each sentence.

2.4 Research Framework

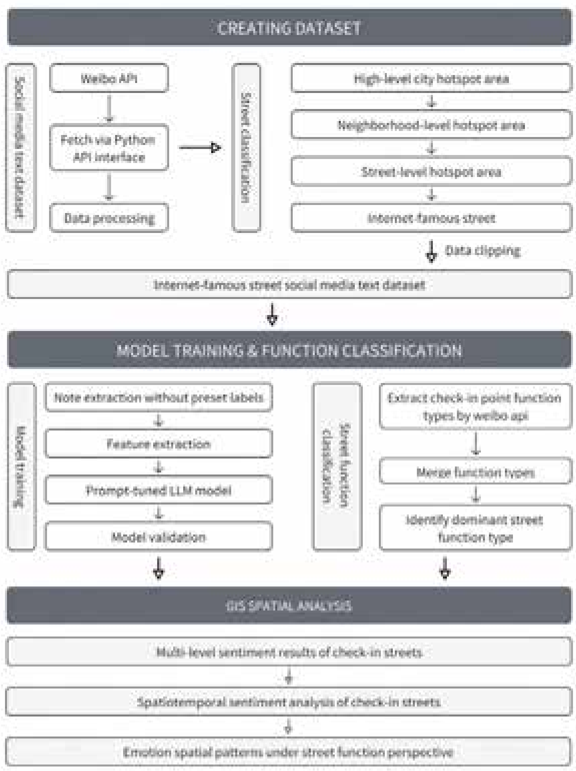


Figure 3: Research Framework (Figure source: self-compiled)

From Figure 3, this study establishes a Weibo text-based framework for identifying and classifying the functions of "internet-famous streets," encompassing three main stages: data collection, model training, and GIS spatial analysis. Data are collected via the Weibo API, functional types are determined using a large language model, and spatiotemporal patterns of internet-famous streets are ultimately visualised from a functional perspective through spatial analysis.

3 Case Study

3.1 Introduction to Nanjing

Nanjing is the capital of Jiangsu Province, a major central city in eastern China, and a megacity within the Yangtze River Delta region. As a historically and culturally renowned city, Nanjing boasts a profound cultural heritage and is historically known as the "Ancient Capital of Six Dynasties" and the "Metropolitan Capital of Ten Dynasties." In addition, the city is celebrated for its natural and urban landscape— "embracing the river and lakes, coiled like a dragon and crouching like a tiger"—and for its spatial structure characterised by "mountains and water interwoven, nested and layered." Immersed in such rich cultural and natural surroundings, Nanjing was named "China's Most Livable City" for the fourteenth time by 2023. This reflects the high level of happiness and satisfaction reported by its residents. The city's cultural and tourism vitality is also notable: during the 2025 May Day holiday alone, Nanjing received more than 12 million tourists. The shared access to high-quality urban space and cultural experiences among residents and visitors further reinforces a sense of belonging and emotional connection to the city.

The Old City of Nanjing, as shown in Figure 4 located in the heart of the urban core, serves as both the origin and continuation of the city's historical and cultural legacy. Its spatial form is framed by the Ming Dynasty's city wall, forming a structure of "outer city enclosure with an inner-city core." The Old City is not only a concentrated area of historic architecture but also a quintessential representation of traditional urban life. With a dense street network and human-scale dimensions, it offers strong walkability and a localised experience. This area integrates multiple functions including cultural tourism, commercial activity, and community life—preserving traditional atmospheres while blending with modern urban elements. Driven by the dynamics of social media, distinctive streets in the Old City—such as Laomendong, Gongyuan Street, and the Qinhuai River waterfront—have gradually evolved into popular "internet-famous" check-in spots, becoming key nodes for emotional expression, cultural identity construction, and urban image dissemination.

Figure 4: The old city of Nanjing (Figure source: self-compiled)

3.2 Hotspot Check-in Streets

3.2.1 Identification of Internet-Famous Check-in Streets

In studies focusing on the identification of internet-famous streets or blocks based on social media data, Zhang Wenquan proposed a method to delineate internet-famous districts. He identified high-popularity roads and blocks and then integrated real traffic networks with social media heat data, outlining check-in districts using a "connect-line-to-polygon" approach (Zhang, W., 2023.). Meanwhile, Yu Yidong et al. divided internet-famous spaces at the city, regional, and block levels into polygonal areas, and further identified the most representative check-in spaces at the block level. Both approaches provide valuable references: Zhang's framework effectively captures road-level connectivity but lacks a broader macro perspective, while Yu's model covers macro to meso-levels but does not extend down to the street scale(Yu, Y., Wang, J., Jiang, X., et al., 2024.).

This study builds on both methodologies and establishes a multi-level identification framework that progresses from city-level hotspot delineation,
district-level hotspots, block-level hotspots, final identification of internet-famous check-in streets, as is shown by Figure 5.

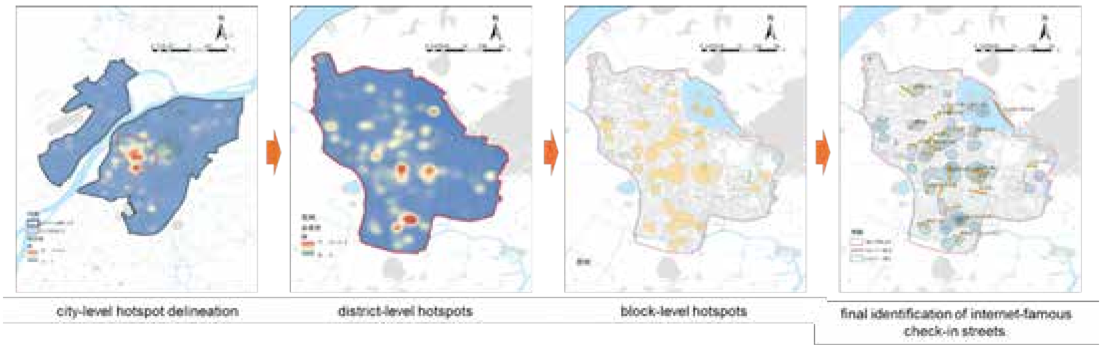


Figure 5: Multi-Level Identification Framework for Internet-Famous Streets (Figure source: self-compiled)

The scope of this study is defined through four hierarchical steps: (1) delineation of city-level hotspot zones, (2) district-level hotspots, (3) block-level hotspots, and (4) the final identification of internet-famous check-in streets.

First, the full dataset of 464,494 check-in Weibo posts with location information from Nanjing's main urban area is filtered by levels. Kernel density analysis of the main urban area reveals that internet-famous check-in zones are highly concentrated in the old city, with smaller clusters in Jiangning and Qixia districts. Due to their lower intensity and scale, the second-level scope is refined to focus on the old city, which contains 285,966 check-in posts.

Kernel density and raster binarization analyses are conducted within the old city to delineate block-level hotspots. Among the many hotspot areas, Xinjiekou, Daxinggong, and the Fuzimiao area show the most intense clustering.

Finally, based on block-level hotspot zones, check-in streets are identified. The top 20 streets and blocks in the old city are selected based on term frequency, along with the top 200 most popular check-in locations. The study integrates these block-level hotspot boundaries with the physical street boundaries to define the spatial extent of check-in streets, excluding overly long streets like Beijing East Road and Zhujiang Road that fall entirely outside hotspot areas. For blocks labeled as area-based check-in types, streets that connect the highest number of check-in points are selected as proxies—e.g., "Zhongshan South Road (Xinjiekou section)" is used to represent the Xinjiekou area.

Moreover, if a road clearly connects multiple check-in spots within a hotspot zone and displays a linear relationship, it is considered a check-in street—for example, Ke Xiang (Kexiang) and Taogu Xincun Road (Taogu New Village Road), which link numerous check-in points. Based on this classification approach, the final set of internet-famous streets within the study area is determined, as is shown in Figure 6 and Figure 7.

Street Name (English)	Check-in Frequency
Zhongshan South Road (Xinjiekou Section)	13,592
Yangtze River Road	6,293
Fuzimiao Pedestrian Street	5,622
Zhujiang Road	5,513
Zhongshan North Road	4,120
Zhongyang Road (Xinjiekou Section)	3,399
Jimingsi Road	3,089
Kexiang Street	3,029
Shanghai Road	2,801
Shiziqiao Pedestrian Street	2,638
East Ring Road of Xuanwu Lake	2,443
Gutong Alley (Laomendong Area)	2,281
Sanshan Street	2,215
Mochou Road	1,958
Yihe Road	1,486
Changfu Street	1,347
Sanpailou Street	1,228
Jiqingmen Road	1,208
Houzaimen Street	1,011
Shanyin Road	1,005
Taogu Xincun Road	932
Fengfu Road	620
Jinyin Street	442

Figure 6: The list of the famous check-in streets (Figure source: self-compiled)

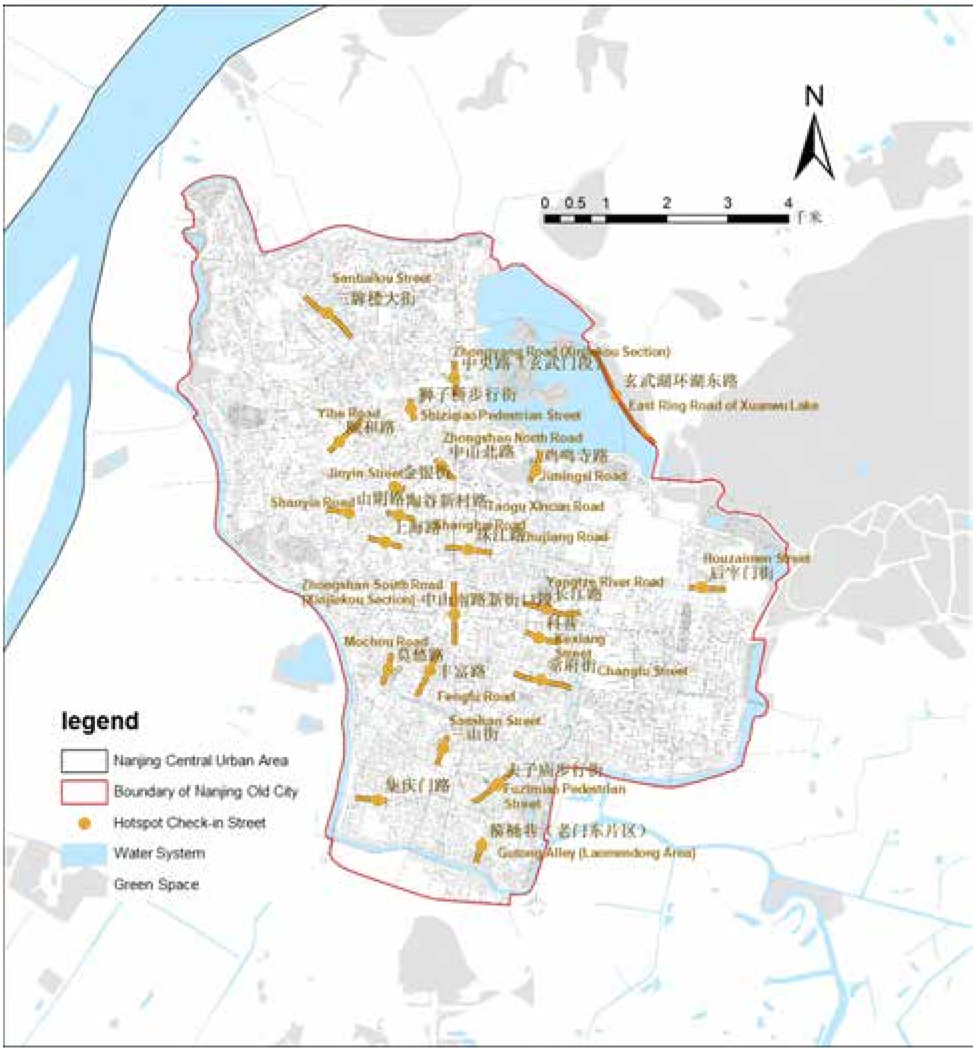


Figure 6: The list of the famous check-in streets (Figure source: self-compiled)

3.2.2 Identification of Check-in Location Functions

The Weibo API provides functional labels for check-in locations; however, these classifications are relatively broad, covering 154 categories such as five-star hotels, dining facilities, road infrastructure, metro station shops, cafés, bars, and more. To streamline the analysis, all location types were manually reclassified into eight major functional categories: education, public services, parks and squares, transportation, commerce, residential, cultural and sports services, and others, as is shown in Figure 7 and 8.

Category	**Classification Criteria**
Education	Includes educational institutions providing various levels of education, such as universities, secondary schools, and kindergartens.
Public Services	Covers facilities related to government, healthcare, and administration, focusing on public service and welfare functions.
Parks and Squares	Refers to open urban spaces with ecological, landscape, leisure, and social functions, including urban parks, pocket parks, and green plazas.
Transportation	Includes transportation infrastructure such as bus stops, metro stations, and railway stations.
Commerce	Encompasses spaces with commercial functions such as retail, dining, business offices, and entertainment or leisure venues.
Residential	Consists of residential-dominant units including commercial housing complexes, affordable housing, and dormitory areas.
Cultural and sports services	Facilities aimed at culture, education, leisure, or physical activities, such as libraries, stadiums, exhibition halls, and cultural centers.
Others	Special or mixed-use spaces that cannot be classified under the categories above.

Figure 7: Functional Types of Check-in Locations (Summarised Based on Weibo API Check-in Labels)

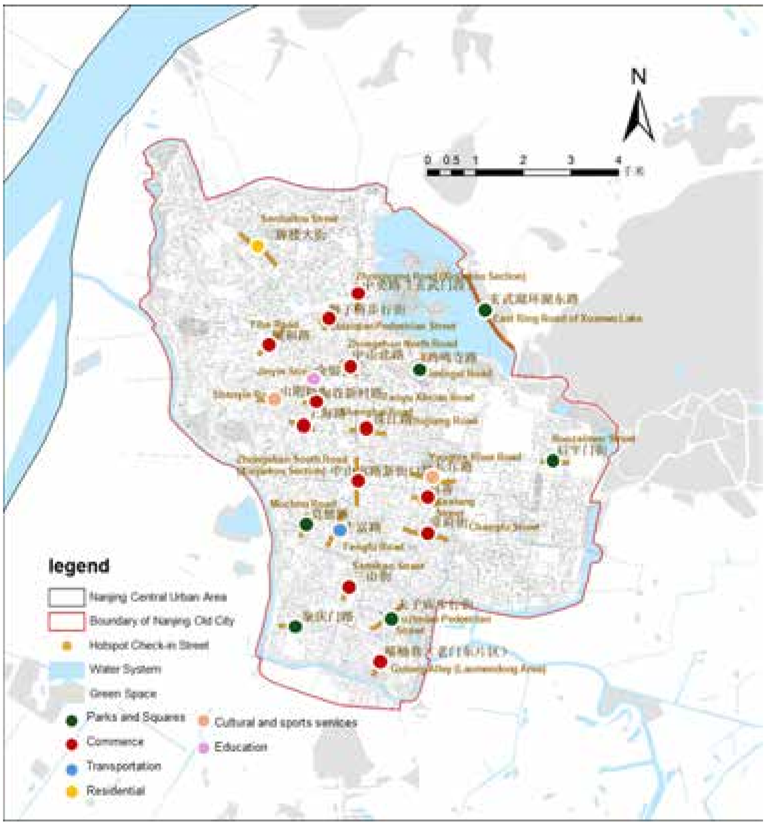


Figure 8: Dominant Functional Type of Internet-Famous Check-in Streets (Figure source: self-compiled)

3.3 Spatiotemporal Analysis of Emotional Patterns in Hotspot Check-in Streets

3.3.1 Overall Emotional Pattern Recognition of Internet-Famous Check-in Streets

Figure 9 illustrates the multi-category and multi-level emotional structure of the internet-famous check-in streets in Nanjing's Old City. Overall, public emotions are predominantly positive, with "happiness" and "affection" forming a strong co-occurrence relationship. Together, they constitute the core positive emotional backbone of the street spaces in the Old City. This emotional structure reflects not only a high level of public approval of the spatial environment but also highlights the streets' appeal as high-quality public spaces that integrate leisure, consumption, and culture, resonating strongly with positive emotions.

Within the positive emotion spectrum, "happiness" tends to convey immediate sensory experiences—such as pleasant scenes or a comfortable atmosphere—while "affection" emphasises long-term spatial preference and emotional attachment. This dual nature suggests that the Old City's streets provide both immediate experiential value and deeper emotional significance.

In contrast, "anticipation," as a secondary positive emotion, flows between several primary emotional nodes, playing a transitional and bridging role. It is positively linked with both "joy" and "affection," but also connects with "neutral" and even "sad" emotions, indicating that when expressing anticipation, users may reveal hopes for future spatial experiences, intertwined with dissatisfaction or desires for improvement in the present environment.

Negative emotions appear more fragmented and complex. Although the overall proportion of negative sources such as "sadness," "disgust," and "anger" is relatively low, their emotional pathways are highly scattered. For example, "sadness" connects not only to "disgust" and "anger" but also to positive emotions like "affection" and "anticipation." This suggests that negative emotions are not merely rejections of space but often represent critical feedback embedded within active urban experiences—such as perceptions of street congestion, over-commercialization, or disorder—interwoven with aspirations for improvement and positive transformation.

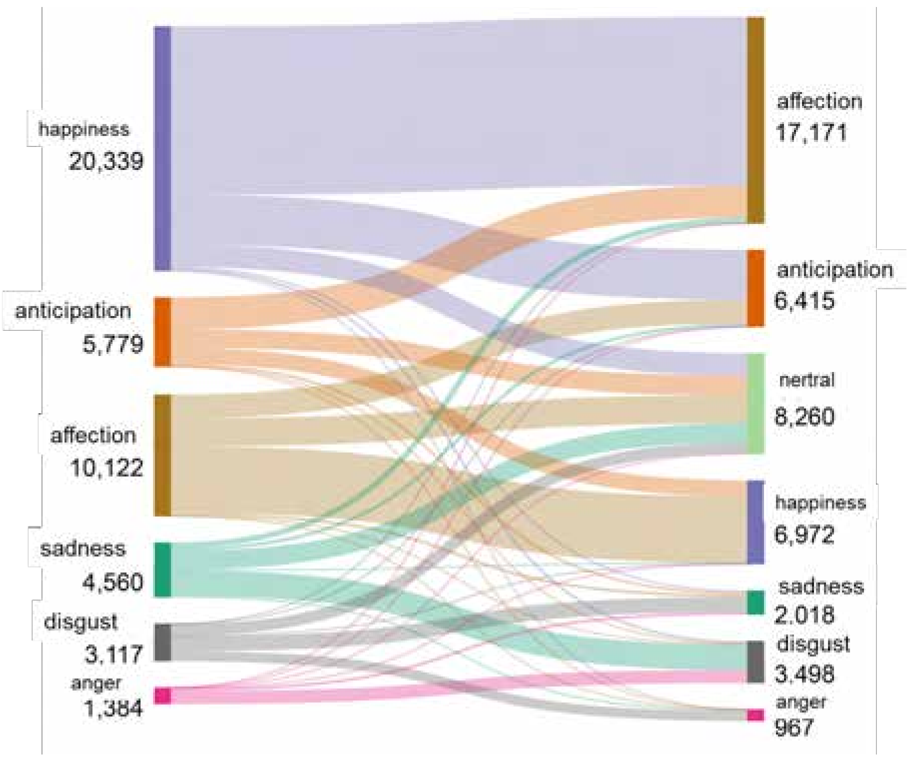


Figure 9: Dominant Functional Type of Internet-Famous Check-in Streets (Figure source: self-compiled)

3.3.2 Overview of Emotional Patterns in Internet-Famous Check-in Streets

Overall, the internet-famous check-in streets in Nanjing's Old City exhibit a predominantly positive emotional pattern, with a generally uplifting spatial atmosphere. Figure 10 illustrates that in most streets, positive emotions account for over 70%, with "happiness" and "affection" consistently serving as dominant sentiments. This pattern indicates a strong foundation of emotional perception among the public—these streets not only fulfill functional needs but also create environments imbued with a sense of pleasure and belonging.

From a finer spatial perspective, the emotion of "affection" highlights spatial identity and cultural attachment. Streets such as Mochou Road, Taogu Xincun Road, and Gutong Alley (Laomendong Area) show a significantly higher proportion of "affection" than other streets. This suggests that these locations carry strong cultural symbolism in the public consciousness and enjoy greater emotional recognition in terms of spatial image, historical memory, and sense of belonging.

A few streets, such as Shanyin Road, Houzaimen Street, and Kexiang Street, show relatively higher proportions of negative emotions like "sadness" and "disgust," potentially reflecting localised issues in functional facilities, environmental ambiance, or congestion experiences.

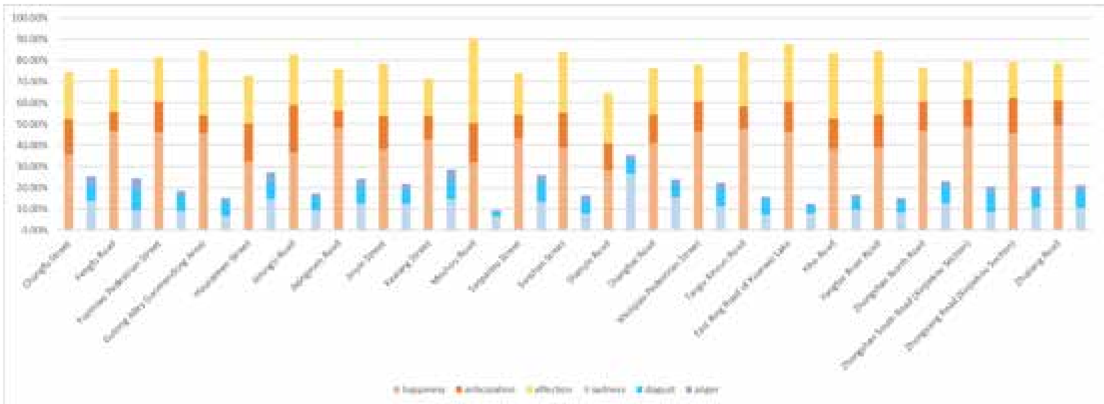


Figure 10: Primary Emotion Categories of Different Check-in Streets (Figure source: self-compiled)

As is shown by Figure 11, streets with different functional types exhibit significant structural differences in emotional expression. Streets characterised by commercial, park and square, transportation, and cultural-sports service functions show a highly consistent pattern of dominant positive emotions. Among these, the emotion "joy" holds an overwhelmingly dominant position across all functional types—particularly in transportation and park/square streets, where it accounts for over 40%, reflecting the public's immediate sense of pleasure and positive experience in such spaces.

In contrast, streets serving educational and public service functions show more pronounced expressions of negative emotions. Specifically, "sadness," "disgust," and "anger" are relatively more prevalent on streets surrounding university areas. This may be linked to issues such as traffic congestion, commercial sprawl, inadequate infrastructure, or restrictive management policies in these zones. Public service streets also display a strong emotional polarization. Although residential streets are similarly dominated by "happiness", they also show relatively high proportions of "disgust" and "sadness," which may be closely related to challenges in old urban residential areas, such as high housing density, lack of supporting public amenities, and spatial aging.

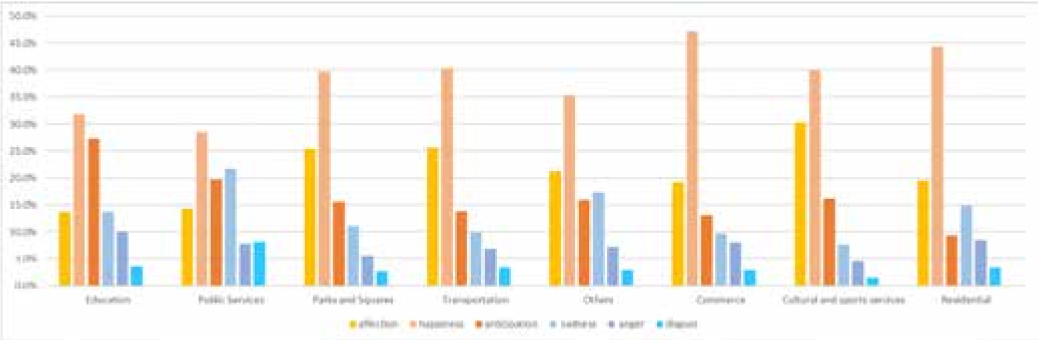


Figure 11: Emotional Patterns from the Perspective of Check-in Location Functions (Figure source: self-compiled)

3.3.3 Spatiotemporal Analysis of Emotional Patterns in Internet-Famous Check-in Streets

(1) Temporal Patterns of Emotions in Internet-Famous Check-in Streets

Figure 12 illustrates the monthly emotional trends of internet-famous check-in streets in Nanjing's Old City from 2019 to 2024. In terms of check-in volume, the overall frequency remained relatively stable between 2019 and 2022, fluctuating between 500 and 1,000 per month, with seasonal peaks typically occurring during summer holidays and national festivals. Since 2023, the check-in volume has seen a steady rise, with significant growth from early 2024 onward. Monthly check-ins have exceeded 3,000, marking a 3–4 fold increase compared to earlier years.

Emotional intensity (blue line) has remained between 0.65 and 0.7, with minimal fluctuation, indicating a strong and consistent level of emotional expression. The absolute value of emotional polarity (green line) has stabilised between 0.55 and 0.6, suggesting that emotional responses are steady and sustained. Emotional polarity (red line) consistently remains positive, fluctuating between 0.3 and 0.4, reflecting a persistently favorable emotional evaluation of the area by the public.

During the COVID-19 outbreak in early 2020, check-in volumes temporarily declined, but emotional indicators remained stable. From 2023 onward, check-in activity rebounded rapidly, with a noticeable surge in early 2024. Overall, despite the sharp increase in activity, emotional indicators remained positive, indicating that the internet-famous streets in Nanjing's Old City have achieved a robust post-pandemic recovery while maintaining a high-quality public space experience amid growing traffic.

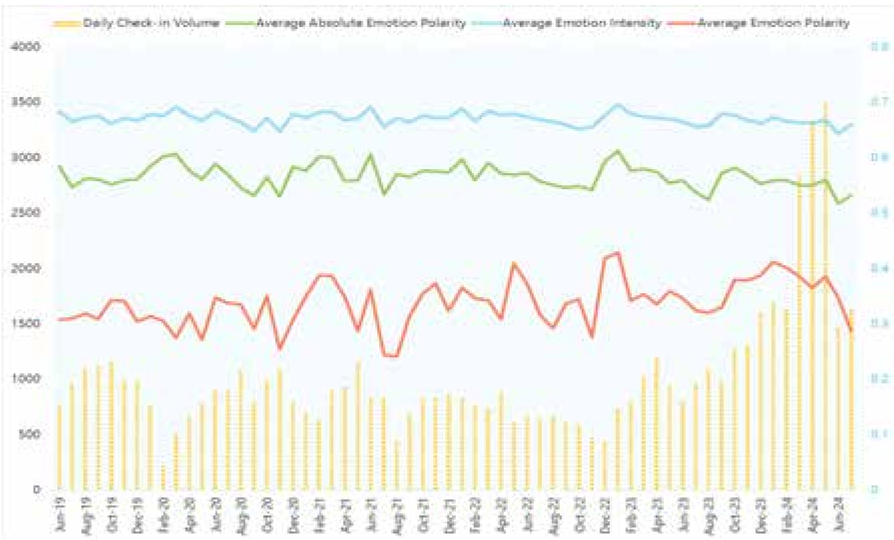


Figure 12: Monthly Analysis of Check-in Frequency, Emotion Polarity, and Emotion Intensity in Internet-Famous Streets (Figure source: self-compiled)

According to Figure 13, based on weekly-scale statistics, the emotional and check-in behaviors on Nanjing Old Town's internet-famous streets exhibit clear cyclical patterns. Firstly, check-in volumes show a typical "weekend effect," with significantly higher activity on Saturdays and Sundays compared to weekdays, reflecting the streets' primary roles in leisure, entertainment, and socializing. Interestingly, check-in volumes on Mondays are slightly higher than other weekdays, possibly due to the "Monday syndrome," as people tend to share their weekend outings and social experiences. During the workweek (Monday to Friday), check-in volumes remain relatively stable, suggesting that these areas attract consistent foot traffic even on weekdays.

In terms of emotional indicators—emotion intensity, polarity, and absolute polarity—there is little variation across the week, with all metrics maintaining a steady level. Even during peak weekend traffic, emotional values do not show notable fluctuations, indicating that these streets possess strong capacity and resilience in spatial management. They consistently deliver a satisfying urban experience across different time periods. Overall, Nanjing Old Town's internet-famous streets demonstrate a high degree of temporal stability in both spatial appeal and emotional perception.

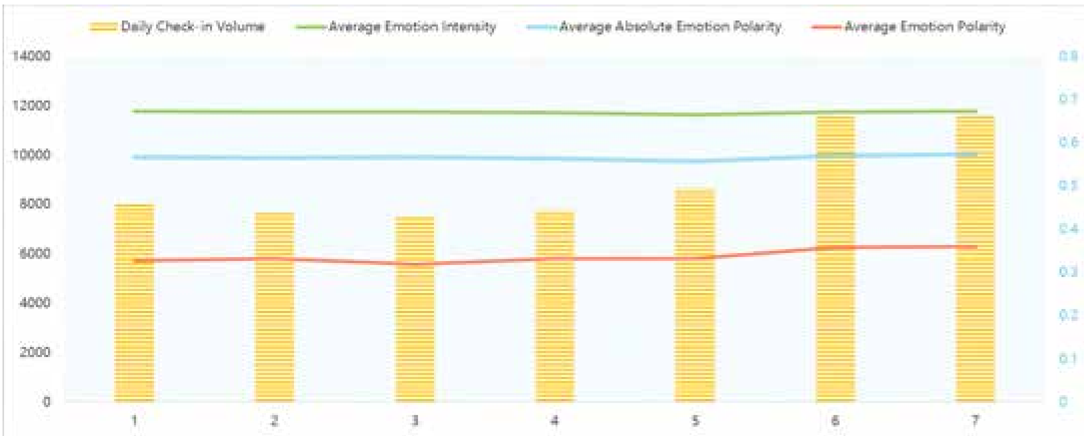


Figure 13: Emotional Patterns from the Perspective of Check-in Location Functions (Figure source: self-compiled)

Based on statistics by the dominant function of streets and on a monthly scale, two key insights emerge:

From the temporal perspective, emotional indicators fluctuated significantly and check-in volumes remained low during 2019–2020, reflecting the impact of the pandemic on urban vitality across all functional areas. In 2021–2022, emotional metrics began to stabilise and check-in volumes gradually recovered, indicating a transitional recovery phase. By 2023–2024, check-ins rose markedly, and emotional indicators remained steady, signaling a positive development trend.

From the functional perspective, commercial streets exhibited the highest level of activity and check-ins, showing sensitivity to holidays and seasonal changes. Due to the large data volume, the emotional indicators were relatively smooth. Parks and squares followed with high activity levels and strong seasonality, performing well particularly in spring and autumn, with stable emotional indicators. Streets with cultural and sports services had moderate activity and generally positive user experiences. In contrast, streets with traffic, residential, or university functions saw relatively low check-in volumes and more noticeable emotional fluctuations, especially under extreme values. Notably, university streets showed negative emotional polarity in the first half of 2020.

Figure 14: Emotional Analysis of Streets with Different Functions from a Monthly Perspective (Figure source: self-compiled)

(2) Spatial Emotional Patterns of Internet-Famous Streets

As shown in Figure 15, the emotional spatial pattern of internet-famous streets in Nanjing's Old Town demonstrates a dual characteristic of "highly clustered positive emotions + locally scattered negative emotions."

Areas dominated by positive emotions are highly concentrated. Red and orange grids representing high emotional polarity are widely distributed in commercial and park/square-type streets. Notable examples include Xinjiekou, Zhongshan South Road, Jiqingmen Road, and Gutong Alley (Laomendong area), where positive emotional polarity is particularly strong and grid coverage density is high. This indicates that such streets not only possess strong commercial appeal but also consistently evoke positive emotional experiences among users. Although streets like Fuzimiao Pedestrian Street and Houzaimen Street show some fragmented expressions of negative emotions, their overall sentiment remains predominantly positive.

Negative emotions are more scattered and localised. University-related streets (e.g., Jinyin Street) exhibit relatively higher proportions of negative sentiment. Transportation-oriented streets (e.g., Fengfu Road) also show high levels of negative emotions, potentially due to factors such as noise pollution, traffic congestion, and accessibility stress. Residential streets (e.g., Sanpailou Street) maintain a certain level of positive emotion but are also interspersed with negative sentiment. Cultural and sports service streets (e.g., Shanyin Road and Changjiang Road) reveal similarly elevated levels of negative emotions, which may be linked to inadequate public facilities, aging infrastructure, or limited capacity for hosting activities—suggesting these spaces may lack adaptability for high-frequency public use.

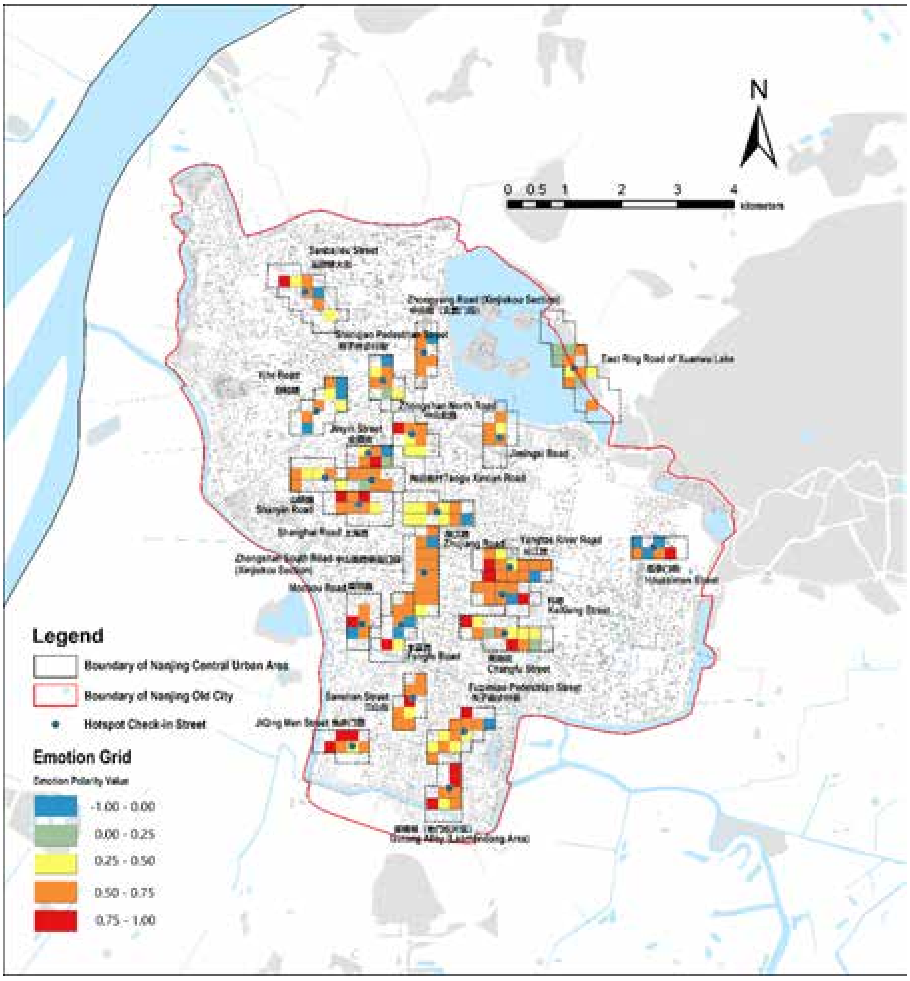


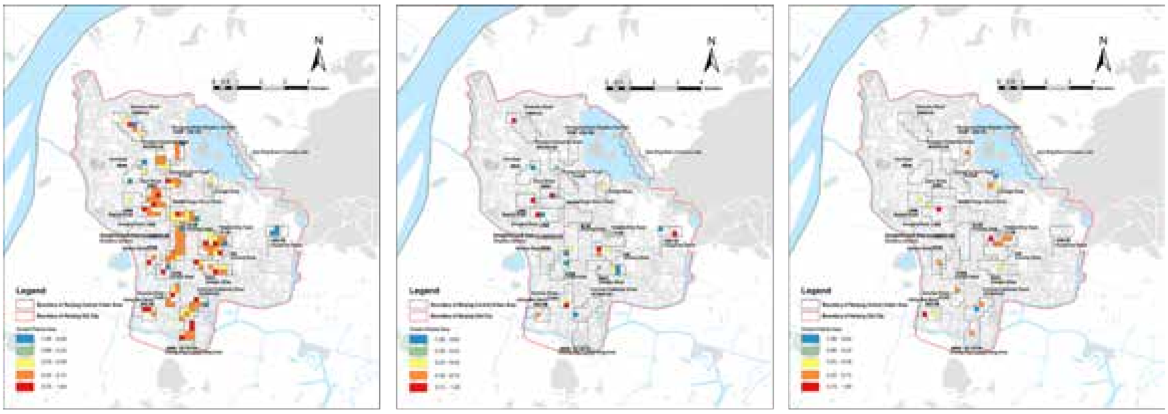
Figure 15: Spatial Visualization Analysis of Emotion Polarity in Internet-Famous Streets (Figure source: self-compiled)

3.4 Emotional Pattern Analysis of Hotspot Check-in Streets from a Functional Perspective

As is shown from Figure 16, from the commercial function perspective, commercial check-in points are the most prominent among Nanjing's hotspot streets. Streets such as Zhongshan South Road (Xinjiekou section), Gutong Alley, Kexiang, and Changfu Street display multiple red and orange grids, representing areas with the strongest positive emotional polarity. Overall, the high proportion of orange grids reflects a well-developed commercial environment and a strong consumer atmosphere in these areas.

From the public service function perspective, the emotional distribution of internet-famous streets in Nanjing's Old City shows a more prominent tendency toward negative sentiment. A higher proportion of blue grids is observed, indicating a pattern of low-value clustering with mixed positive and negative emotions. Negative emotions are dominant, and spatial consistency is relatively weak. Low emotional polarity zones are mainly concentrated along streets such as Shanyin Road, Changjiang Road, Zhongshan North Road, and Huanhu East Road of Xuanwu Lake, suggesting certain negative perceptions regarding the spatial environment, functional amenities, or user experience of public service facilities.

From the perspective of cultural and sports services, the emotional spatial distribution of hotspot check-in streets shows a more dispersed pattern of positive sentiment. Overall, red and orange grids are spread across multiple streets, forming a generally positive emotional landscape. High-value zones are mainly concentrated along Gutong Alley, Taogu Xincun Road, and Kexiang. In contrast, grids representing negative emotions (blue or green) are relatively few and scattered, primarily appearing in limited areas such as Zhongshan North Road and the Xuanwumen section of Zhongyang Road. Although the distribution of positive emotions in cultural and sports service spaces lacks strong spatial continuity, most check-in locations maintain a high level of positive emotional expression, indicating strong positive spatial perception.



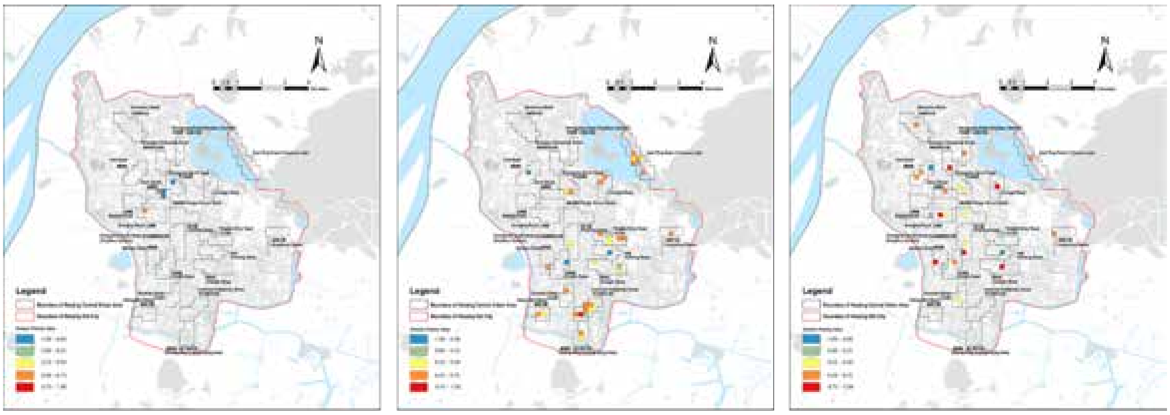
Commercial Function | Public Service Function | Cultural and Sports Service Function

Figure 16: Spatial Visualization Analysis of Emotion Polarity in Internet-Famous Streets from Commercial, Public Service, Cultural and Sports Service Function (Figure source: self-compiled)

From the perspective of university-related functions, the emotional spatial distribution of internet-famous check-in streets in Nanjing's Old City is relatively limited. Overall, check-in points associated with universities are few and sparsely distributed. The primary low-emotion grids (blue and light blue) are concentrated in areas surrounding Jinyin Street and the Xuanwumen section of Zhongyang Road, indicating more prominent expressions of negative emotions.

From the perspective of parks and squares, both tourists and residents in Nanjing show high levels of satisfaction with such spaces. Red and orange grids are densely concentrated in areas such as the surroundings of Xuanwu Lake, Laomendong, and Mochou Lake, suggesting that these park and square spaces receive strong positive emotional feedback in public check-ins. In contrast, more negative comments are found around Yihe Road and Kexiang, which may be linked to crowd congestion, insufficient maintenance, lack of facilities, or conflicts with nearby developments.

From the perspective of transportation functions, the emotional spatial distribution of internet-famous streets in Nanjing's Old City is generally dominated by positive sentiment, with fewer negative expressions. Most transportation-related check-in points fall within orange and yellow grids, indicating a reasonably planned transportation layout and a relatively pleasant travel experience. However, localised high negative emotion zones are concentrated around Yihe Road and Kexiang, reflecting potential inconveniences or congestion issues in traffic conditions or accessibility in these areas, as is shown in Figure 17.



Education Function — Parks and Squares Function — Transportation Function

Figure 17: Spatial Visualization Analysis of Emotion Polarity in Internet-Famous Streets from Education, Parks and Squares and Transportation Function (Figure source: self-compiled)

4 Discussion and Conclusion

4.1 Discussion

This study provides an in-depth analysis of the emotional spatial patterns of internet-famous check-in streets in Nanjing's Old City. The findings show that public sentiment is predominantly positive, with “joy” and “affection” being particularly prominent. This emotional structure reflects a high level of public approval toward the street environment and indicates that these spaces offer both immediate experiential value and long-term emotional attachment. For example, Xinjiekou, as a core commercial area, shows exceptionally high levels of positive emotion, highlighting strong public resonance with its vibrant commercial atmosphere.

A detailed analysis of emotional patterns further reveals that while negative emotions account for a smaller portion overall, they exhibit fragmentation and complexity. Emotions such as “sadness” often interact with positive ones like “anticipation” and “affection,” indicating that critical feedback from the public is often accompanied by expectations for spatial improvement. For instance, although Kexiang Street demonstrates generally positive emotions, there are noticeable localised expressions of negativity, likely due to crowding and inadequate facilities.

From a spatiotemporal perspective, the emotional activity on internet-famous streets in the Old City shows clear cyclical characteristics, with higher emotional engagement during weekends and holidays, suggesting that these areas serve primarily recreational, social, and cultural functions. Monthly and yearly trends further demonstrate the streets' emotional resilience and recovery—especially after the impacts of the COVID-19 pandemic—with a notable revival in vitality from 2023 onward, and stable sentiment levels, reflecting the rapid recovery capacity of urban public spaces after disruptive events.

This study offers two key methodological innovations: First, it incorporates large language models (LLMs) for emotion analysis, significantly enhancing the accuracy and efficiency of detecting emotional patterns in complex social media texts. Second, while most previous research has focused on citywide emotional mapping, this study adopts a street-level perspective, uncovering fine-grained interactions between public sentiment and spatial function types at the micro-scale. This shift in scale not only enriches the field of emotional geography but also offers precise decision-making support for urban planning and spatial optimization.

Future research could further extend the application of emotion analysis technologies, exploring the interaction between emotional patterns and spatial optimization strategies, thereby advancing urban governance toward greater refinement and human-centered development.

4.2 Conclusion

From a functional perspective, the internet-famous check-in streets in Nanjing's Old City exhibit clear spatial emotional distribution characteristics. Commercial streets—such as Xinjiekou, Zhongshan South Road (Xinjiekou section), Shiziqiao Pedestrian Street, Gutong Alley, Taogu Xincun Road, and Mochou Road—are dominated by positive emotional clustering, forming the core zones of highest emotional polarity. Streets associated with parks and squares—such as Fuzimiao Pedestrian Street, Houzaimen Street, and the East Ring Road of Xuanwu Lake—also feature mainly positive emotions, though some areas display scattered negative sentiment.

Cultural and sports service streets—such as Shanyin Road and Changjiang Road—exhibit a bipolar pattern, with both positive and negative emotions relatively balanced. University-oriented streets—such as Jinyin Street and the Xuanwumen section of Zhongyang Road—show a more pronounced distribution of negative emotions. Transportation-oriented streets—such as Fengfu Road—present a stronger concentration of negative emotions. Residential streets—such as Sanpailou Street—display a mix of both positive and negative emotions.

Overall, commercial and park/square streets emerge as primary hubs of positive sentiment, whereas streets associated with universities, transportation, and some residential or cultural service functions exhibit relatively more negative sentiment. The emotional spatial pattern shows a clear functional differentiation driven by street type.

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