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Research on the Influencing Mechanism of Historic Urban Landscape Characteristics on Public Sentiments and the Spatio-temporal Differentiation Patterns
—A Case Study of Shaoxing Ancient City in Zhejiang Province, China

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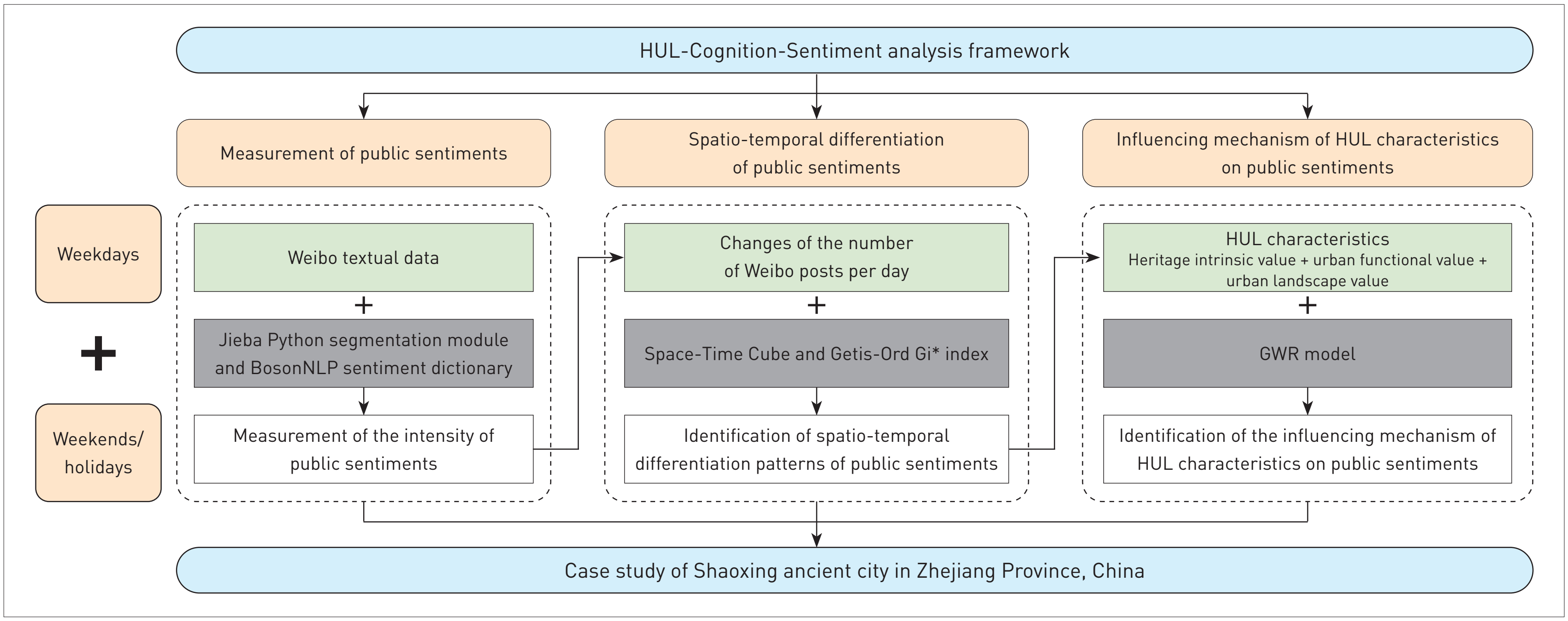
GRAPHICAL ABSTRACT



ABSTRACT

Combining research methods such as semantic analysis and Space-Time Cube, this paper proposes a "historic urban landscape–cognition–sentiment" analysis framework, covering aspects of heritage intrinsic value, urban functional value, and urban landscape value, and reveals the influencing mechanism of the characteristics of historic urban landscape (HUL) on public sentiments and the spatio-temporal differentiation patterns through the case study of the Shaoxing ancient city in China. The research findings include that different HUL characteristics had differentiated effects on public sentiments, and the effect of a same HUL characteristic on public sentiments varied between weekdays and weekends/holidays, and among different HULs. On weekends/ holidays, public sentiments were more influenced by the intrinsic value factors of HUL (e.g., heritage level, heritage age), whereas on weekdays, they were more affected by urban functional value factors, and urban landscape value factors played a greater role in arousing people's positive sentiments. This study aims to provide scientific references for enhancing public perception and emotional experience in urban spaces and for identifying potential spatial improvement opportunities in historic cities.

KEYWORDS

Historic Urban Landscape; Public Sentiments; Weibo Check-in Data; Spatio-temporal Differentiation Patterns; Space-Time Cube; Historic Urban Landscape–Cognition–Sentiment Analysis Framework

HIGHLIGHTS

- Innovatively proposes "HUL–Cognition–Sentiment" analysis framework, and systematically explores the influencing mechanism of HUL characteristics on public sentiments
- Studies the spatio-temporal differentiation patterns of public sentiments from the dimensions of HUL intrinsic value, urban functional value, and urban landscape value
- On weekends/holidays, public sentiments were more influenced by the intrinsic value factors of HUL, while on weekdays were more affected by urban functional value and urban landscape value factors

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1 Introduction

In 2011, UNESCO issued *The UNESCO Recommendation on the Historic Urban Landscape* ("*The Recommendation*" hereafter), introducing the concept of "historic urban landscape" (HUL). HUL is defined as "the urban context and its geographical setting taking into consideration the historical layering of cultural and natural values and attributes"[1]. This definition emphasizes the historical layering of cultural and natural legacies, as well as the dynamic superimposition of current urban development, where culture is seen as the driving force of the city, nature as its carrier, and urban landscape as the result of such interactions and evolution[1]. *The Recommendation* also highlights the need to research the public's collective memory and universal consciousness in the preservation of HUL[2]. The cognitive theory of emotion posits that emotions are products of the interactions between people and the environment[3]. Recent studies have gradually unveiled the complexity of public sentiment perception, which is closely related to the attributes of HUL and the image of heritage sites[4].

It is noteworthy that ancient towns or historic cities, as an important subclass of HUL, have garnered increasing attention in recent years[5][6]. These cities and towns enjoy rich historical and cultural assets but also face various challenges brought by globalization and modernization, especially the exacerbated cultural homogenization and identity loss of HUL. The root cause of this issue lies in an overemphasis on production efficiency under short-sighted urban development ideologies, which neglect human needs and user experience in sustainable urban development[7].

In recent years, public perception and emotional experience of physical environments have become a focal point in urban studies[8], which, however, is less combined with HUL in academic efforts. Existing scholarly research predominantly focuses on public perception on the image of HUL, with subjects such as visual image perception of HUL based on digital footprints[9], evaluation of HUL based on online reviews[10], and heritage identity perception[11]. In these studies, public sentiments and feelings are merely considered as indicators or representations of HUL perception, and their relationship with HUL preservation and sustainable development has not been fully explored. Therefore, this study proposes an "HUL–Cognition–Sentiment" framework that analyzes the influencing mechanisms of HUL characteristics of historic cities on public sentiments, hoping provide scientific references for enhancing public well-being and identifying potential improvement opportunities for historic cities.

2 Literature Review on Public Sentiments From the Perspective of HUL

2.1 Public Cognition and Sentiments From the Perspective of HUL

HUL not only encompasses physical spaces but also serves as a vessel for cultural and public historical memories, providing a profound and significant context for contemporary human life[12]. HUL also involves intangible values of historic cities. Social values, community identity, and civic pride are not only reflected in monuments and buildings, but also embodied in the places and moments of people's collective life[13]. From the perspective of HUL, people can form deep emotional connections with the places they live in[14]. Rossana Bonadei et al. noted that when the public interact with HUL, they would have their own perception based on their aesthetic, emotional, cultural, and relational values or the experiences attached to it[15]. For example, historians might emphasize the origins of HUL, while architects often highlight its artistic value and the use of specific materials. In this context, understanding public sentiments about HUL and how the perception influences their emotional experience becomes critical.

Since the formal introduction of Emotional Geography in 2001[16], emotions have shifted from being purely subjective mental issues to broader socio-cultural fields, generating spatial, open, and relational emotions[17]. Public emotion, as people's collective feelings and attitudes towards a public matter or event, is "often the product of repeated place interactions and experience"[18]; while, perception can reveal the extent of public cognition regarding the given public matter or event. Richard Stanley Lazarus's cognitive theory of emotion further underscores the relationship between cognition and emotion, positing that "emotions are the products of appraisals"[19]. This implies that the public's cognitive assessment of HUL, influenced by sensory reception and personal experience, directly affects their emotions. In summary, cognition is the basis of sentiments, and sentiments are an extension of cognition[4]; the public's cognition and sentiments about HUL constitute a dynamic, interactive process. To better protect and utilize HUL, and to ensure that HUL planning and management align more closely with public needs and desires, it is essential to deeply understand the process of how the public's cognition and sentiments are generated concerning HUL.

2.2 Methods for Measuring Public Sentiments

With the rapid advance of location-based services (LBS) technology, it is able to actively or passively obtain and collect information about public sentiments and attitudes with sensing devices and positioning technologies, enabling the measurement and visualization of public sentiments within spatio-temporal units.

Typically, active measurement methods require the public's cooperative participation[20]. For example, questionnaires[21] can be used to collect in-depth insights into the public's emotional responses to a specific urban landscape; laboratory observations[22] and wearable sensing devices[23] can be used to capture real-time sentiment changes in urban spaces. These methods provide urban planners with direct and detailed feedback, allowing them to better understand the public needs and desires. In contrast, passive measurement methods do not require the public's active participation[20]; aided by advanced big data semantic analysis technology, including various lexicons or machine learning algorithms[24], social media data from platforms like X (former Twitter)[25] and Weibo[26] offer new opportunities for passive measurement and visualization of public sentiments. Such unstructured data, with user-posted spatial information, contain extensive textual information that can reflect citizens' real sentiments (e.g., happiness, sadness, fear, disgust, anger, surprise)[27], helping reveal the spatio-temporal differentiation patterns of public sentiments. This approach has been widely applied in urban planning, for example, to study citizens' sentiments in response to public safety incidents[28] and public sentiment changes towards the government following terrorist events[29].

2.3 The Influence of HUL Characteristics on Public Sentiments

HUL is not a static built-up setting but the result of continuous dynamic layering, representing a complicated, continuously adaptive socio-ecological system[30]. Sentiments are influenced by both activities and places, and the spatio-temporal sequences of activities and places are in turn influenced and constrained by emotions[31]. This means that public sentiments of the same HUL can vary significantly across different times and spaces. Jia Jian et al. pointed out that the physical characteristics, spatial scale, and functional organization of the built-up setting would directly influence public sentiments and experiences[31]. Zexin Lei et al. provided a theoretical framework, summarizing the criteria of HUL evaluation system into three aspects, namely protection status, intrinsic value, and integration with the city[32].

At the aspect of intrinsic value, some studies have revealed how the intrinsic value of HUL influences public perception on historic cities, highlighting its core role in establishing emotional connections and fostering cultural identity. For example, a study using wearable devices to survey public emotional arousal in Jerusalem found that areas with the greatest protection value, such as the Temple Mount and the Wailing Wall, showed the highest levels of positive sentiments among the public[33]. Additionally, research on public sentiments about landscapes with special values, such as dark heritage sites like Auschwitz, has also gained widespread attention in academia[34].

However, research on the influence of the other two aspects, protection status and integration with the city, on public sentiments remains limited. First, the protection status of historical buildings and relics can influence people's identity and sense of belonging: well-preserved heritages may evoke the public's pride and honor, while neglected or damaged sites may lead to feelings of loss or anger[35][36]. The specific mechanisms of these effects, however, are still underexplored. Second, the degree of HUL integration with the modern urban environment might affect the public's emotional experiences, which is similar to the influencing mechanisms of built environment that urban geography has long focused on. Zhuoran Shan et al., by collecting POI and Weibo data from the main urban areas of Wuhan, verified that the densities of transportation facilities, commercial outlets, jobs, entertainment facilities, public service facilities, and outdoor recreational spaces significantly affect residents' sentiments[26]. Miguel Jesús Medina-Viruel et al. also confirmed that there is a significant positive correlation between entertainment and the accessibility and convenience of facilities with tourists' positive sentiments around the heritage sites of Úbeda and Baeza in Spain[37]. Yali Yang et al. found that, for the public in Barcelona, sentiment-related Twitter posts tend to cluster around tourist attractions or recreational spots[18].

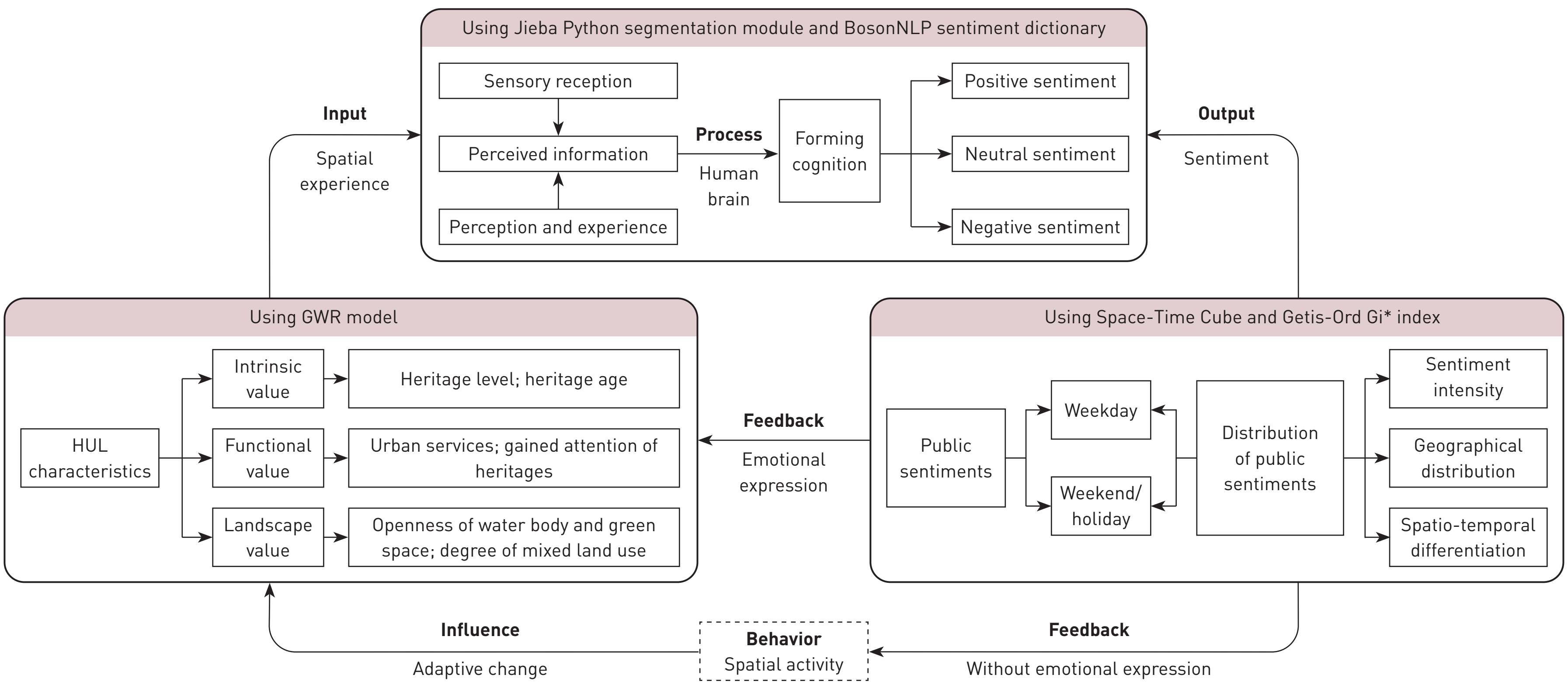
In summary, although cities are considered dynamic and cumulative products of spatio-temporal changes, the influencing mechanisms of HUL characteristics on public sentiments remain insufficiently explored. Filling the gap, this study uses social media big data to measure public sentiments and to reveal the influencing mechanisms of which by HUL characteristics. This research aims to provide a reference for theoretical and practical efforts for identifying potential areas for improvement in historic cities and the development of optimization strategies in urban planning and management.

3 The HUL–Cognition–Sentiment Analysis Framework

To elucidate the dynamic evolution process from identifying HUL characteristics to the public's emotional responses, this study constructs an HUL–Cognition–Sentiment (HCS) analysis framework (Fig. 1), which consists of three main parts.

1) Analysis of HUL characteristics. This study employs the Geographically Weighted Regression (GWR) model to reveal and examine the core characteristics of HUL in dimensions of heritage intrinsic value, urban functional value, and urban landscape value. Intrinsic value considers heritage grade and age to represent HUL preservation status and historical value. Urban functional value selects urban services and gained attention of heritages to represent the interactions between HUL and other functional structures in the city. Urban landscape value examines the openness of water bodies and green spaces and the degree of mixed land use to represent the

1. HCS analysis framework.



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visual and aesthetic integration of HUL with natural and urban environments.

2) Analysis of public sentiments. This study used Jieba Python segmentation module and Sentiment Lexicon to dissect textual big data from Weibo, combine individuals' direct feedback to HUL with deeper cognitive experiences, and empirically quantify the transformation process from sensory responses to emotional cognition—the public's sensory reception and experiences when identifying HUL characteristics generate sensory information, which is processed by the brain into cognition. In this research, the cognition results are expressed as positive, neutral or negative emotions.

3) Analysis of spatio-temporal distribution of public sentiments. Based on the measurements of public sentiments, a comparative study was conducted on the intensity and geographical distribution of sentiments during weekdays and weekends/holidays. Space-Time Cube and Getis-Ord Gi* index were used to reveal the spatio-temporal differentiation patterns of sentiments, exploring the changes and patterns of public sentiments. People's sentiments determine their active or passive feedback towards HUL, and in turn the assembly of these spatial behaviors dynamically influences the formation and evolution of HUL[38]. There are two main paths for public feedback on HUL: direct emotional expression and spatial behavior without emotional expressions. For the former, it can be the public's favoritism or dissatisfaction with HUL expressed through platforms such as social media, which can directly influence HUL conservation and development strategies; while the latter, for instance, frequent visits to a particular HUL, can reflect the attractiveness of a given HUL to the public, which will in turn influence urban planning and cultural heritage management.

Combining these three parts, the HCS analysis framework provides a multi-dimensional perspective to explain the generation process of public sentiments about HUL. Demonstrating with the case of the Shaoxing ancient city in Zhejiang Province, China, this paper employs the HCS framework and Weibo big data, along with multiple spatial analysis methods, and explores the interactions between HUL and public sentiments.

4 Study Area and Research Methods

4.1 Study Area

The Shaoxing ancient city in Zhejiang Province was initially constructed in 490 BC, boasting a history of over 2,500 years, as an area having evolved continuously through different historical periods①. The study area is defined by the outer banks of the ring moat in the Yuecheng District of the city, covering an area of approximately 9 km^2[39]. The ancient city also enjoys unique water town landscapes characterized by "three mountains, hundreds of bridges, and thousands of winding alleys with interwoven waterways," as well as a wealth of historical and cultural heritages. According to the *Shaoxing Historical and Cultural City Protection Plan (2021–2035)*, the ancient city includes eight historical and cultural neighborhoods: Lu Xun's Former Residence, Yuezi Town, Bazi Bridge, the Former Residence of Calligraphy Sage, Xixiao River, Shimenkan, Qianguan Alley, and Xinhe Lane, with a total of 62 heritage protection units of varing grades (Fig. 2).

The study utilized the ArcGIS Pro platform to construct a spatial analysis grid with cells of 20 m × 20 m each. Spanning from August 1, 2022, to January 31, 2023, the study period supported the comparative analysis between weekdays and weekends/holidays.

4.2 Data Collection and Processing

4.2.1 Weibo Check-in Data

Weibo check-in data include the textual content and timestamp and location information generated when users perform the function of check-ins. The study collected Weibo check-in data within the study area from August 1, 2022, to January 31, 2023. Each piece of data included user ID, posted text, time of posting, and geographic coordinates (Table 1). After eliminating duplicate,

① Data source: official website of Shaoxing Municipal People's Government.

2. Study area.

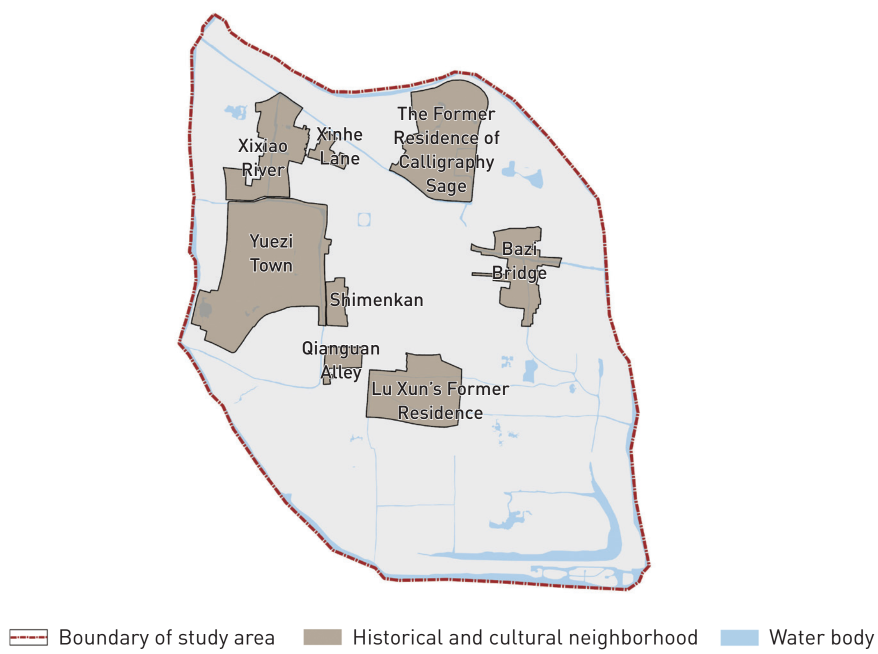

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Table 1: Examples of Weibo check-in data

User	Textual data	Release time	Longitude	Latitude
A	"Xu Wei Art Museum is a surprise in Shaoxing. It has a sense of ideal pureness, and I like the building so much."	2022-08-12	120.574°E	29.998°N
B	"Extreme passion is spontaneous! Everyday on the road of enthusiasm, with light in the eyes and a beautiful future..."	2022-10-01	120.582°E	30.004°N
C	"Walking around the Cangqiao Zhijie Street, where I lived for two years many, many years ago. This is an old street, every morning the seniors chatting on the street and used to be busy all day long. Now there are various small shops including several cafes, with quite a charming style."	2022-11-17	120.573°E	30.005°N
D	"Kong Yiji has not been the figure of sadness, but has become a celebrity for fennel beans."	2023-01-07	120.578°E	29.995°N

blank or irrelevant data (such as purchasing agents and house rentals) and unrelated web links, 8,151 pieces of valid check-in data were obtained.

4.2.2 Data of HUL Characteristics

The data of HUL characteristics included POI data, historical heritage data, and remote sensing imagery data. POI data, collected from Amap from October 2 to 4, 2022, covered recreational and entertainment facilities, medical service facilities, and transportation facilities. Historical heritage data included information of the protection grade, construction era, and geographic location of the heritage sites within the study area, sourced from the *Shaoxing Historical and Cultural City Protection Plan (2021–2035)*. The study also obtained remote sensing data with a resolution of 0.5 m from Google Earth, taken on June 12, 2021, to identify land cover types and spatial layouts within the study area. With the aid of ArcGIS Pro platform, six land cover types were identified: green space, water body, bare land, building, road, and impervious surface, and 20 ~ 30 grid cells of each type were randomly selected for validation.

4.3 Research Methods

4.3.1 Measurement of Public Sentiments

The study employed Python to perform sentiment analysis of the textual content of the Weibo check-in data. First, each piece of text was segmented using the Jieba library, Python's Chinese word segmentation module[40], and the frequency of each word was counted. Then, the study utilized the open-source BosonNLP sentiment dictionary[41] to determine the value assignment of the sentiments. This dictionary contains approximately 120,000 sentiments, and each of them with an associated score (Table 2). Positive or negative scores reflect the nature of the sentiment, i.e., positive, neutral or negative sentiments, and the absolute value of the score indicates the intensity of the sentiment. Using the geographic location information from the check-in data, the study applied the Inverse Distance Weighting (IDW) interpolation[42] method to perform spatial interpolation of the sentiment scores for each piece of check-in data, through which the distribution of public sentiments within the study area can be obtained. The calculation formula is as follows:

$$\hat{Z}(X_j) = \sum_{i=1}^{N} \alpha_i Z(x_i) \, , \tag{1}$$

where $\hat{Z}(X_j)$ is the predicted score of the sentiment at location j; $Z(x_i)$ is the measured score of the sentiment at location i; and α_i is the reciprocal of the distance between the predicted location j and the known location i.

4.3.2 Measurement of the Spatio-temporal Distribution of Public Sentiments

The visualization method of Space-Time Cube was employed to reveal the spatio-temporal differentiation patterns of public sentiments within the study area. Space-Time Cube is a three-dimensional data cube, and each cube unit has a fixed position (x, y, t), where t represents the time step, i.e., the difference between two consecutive time points and (x, y) represents the spatial location of the unit[43][44] (Fig. 3). Referring to the grid cells,

Table 2: Examples of word value assignment by the BosonNLP sentiment dictionary

Category	Word	Assigned value
Positive	Content	2.1
	Joyful	2.6
	Happy	2.6
	Peaceful	0.8
Negative	Irritable	−4.4
	Disturbed	−6.5
	Scared	−4.1
	Unscrupulous	−4.1
Neutral	According to	0.0
	Phenomenon	0.0
	South Zone	0.0
Adverb of degree	Remarkably	1.8
	Very	1.8
	A little	0.7
Deactivated word	Too; also; thus; besides	Eliminated, no assigned value

NOTE
The research adopted the already assigned values by the BosonNLP sentiment dictionary.

the cube unit of the Space-Time Cube set to a length of 20 m and the time step set to one day.

Subsequently, the study used the Getis-Ord Gi* index for hotspot clustering analysis. This index can reflect the differentiation of the levels of public sentiments between a given zone and its surrounding areas, so that to identify hot and cold spots, i.e., the clustered and dispersed zones of public sentiments. The calculation formula is as follows[43]:

$$G_i^* = \frac{\sum_{j=1}^{n} w_{i,j} x_j - \bar{X} \sum_{j=1}^{n} w_{i,j}}{S \sqrt{\dfrac{\left[n \sum_{j=1}^{n} w_{i,j}^2 - \left(\sum_{j=1}^{n} w_{i,j}\right)^2\right]}{n-1}}} , \tag{2}$$

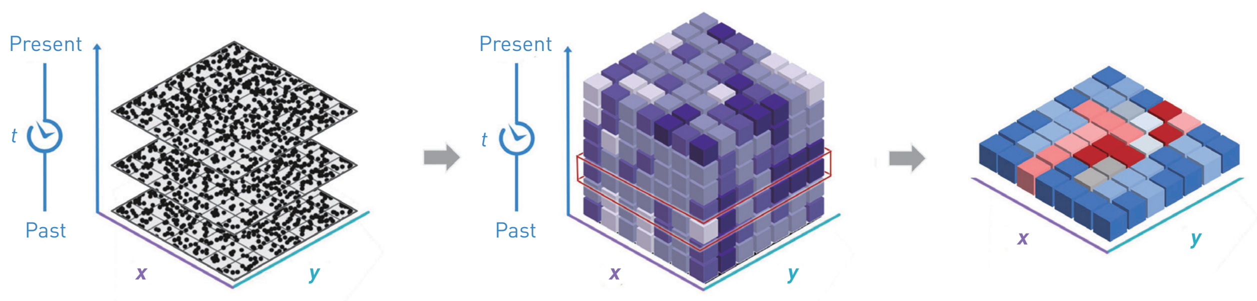
where i represents a given grid cell; j represents all its surrounding grid cells; x_j is the average score of public sentiments within j; $w_{i,j}$ is the spatial weight between grid cells i and j, calculated using the default distance-based algorithm on the ArcGIS Pro platform to measure the spatial correlations of public sentiments; and n is the total number of grid cells. When the Getis-Ord Gi* result is positive and significant, the higher the value is, the closer the positive sentiments cluster; conversely, when the result is negative and significant, the lower the value is, the closer the negative emotions cluster.

4.3.3 Analysis of the Influencing Mechanism of HUL Characteristics on Public Sentiments

The study used the GWR model to examine the influencing mechanism of HUL characteristics on public sentiments. Unlike traditional global regression models (e.g., Ordinary Least Squares), GWR model can effectively explain local differences in regression coefficients[45], i.e., supporting the refined analysis of the relationships between the HUL characteristics and public sentiments at a smaller scale and to identify the ones significantly affecting public sentiments. The model expression is:

$$y_i = \sum_{j=1}^{k} \beta_k(u_i, v_i)\, x_{ij} + \varepsilon_i , \tag{3}$$

where y_i is the average score of public sentiments at the unit i within the Space-Time Cube; (u_i, v_i) is the geographical coordinates of unit i; x_{ij} is the independent variable j for public sentiment score of unit i, i.e., HUL characteristics in this study (see Section 6);



3. Space-Time Cube.

$\beta_k(u_i, v_i)$ is the regression coefficient for the k-th independent variable of unit i; and ε_i is the residual error.

5 Spatio-temporal Differentiation Patterns of Public Sentiments in the Shaoxing Ancient City

Analysis results (Table 3) indicate that public sentiments in the Shaoxing ancient city had an average score of 6.983, and a mean intensity value of 7.160. This displayed an overall positive sentiments among the public, and the negative sentiments did not dominate, suggesting that the public in the study area tended towards positive emotional experiences.

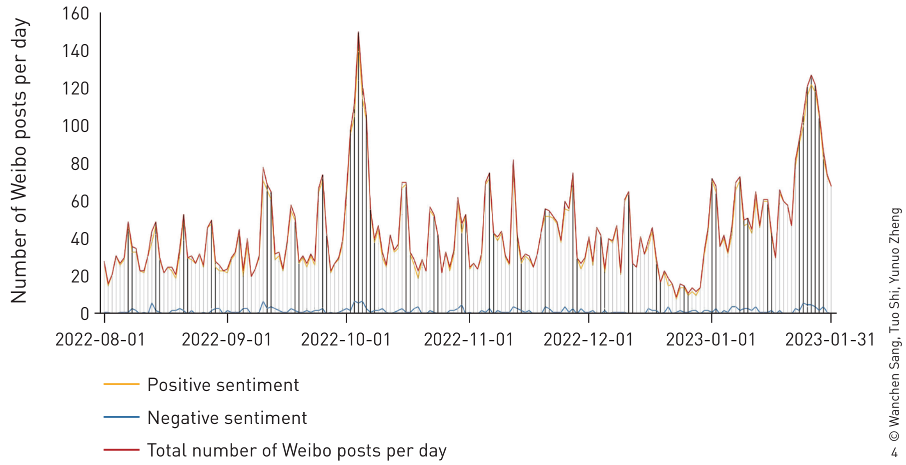
The study further conducted a detailed analysis of the number and temporal variation of the Weibo posts, and found that there were significant peaks in early October 2022 and late January 2023 (during the National Day holiday and the eve of the Spring Festival, respectively). While, there was a noticeable decrease around the end of December 2022, possibly due to the pandemic outbreak in China at that time, when the public's outings and social media usage were reduced. The fluctuations in posting volume were relatively small in other months. Additionally, the results show that the number of posts on weekends/holidays was significantly higher than that on weekdays (Fig. 4).

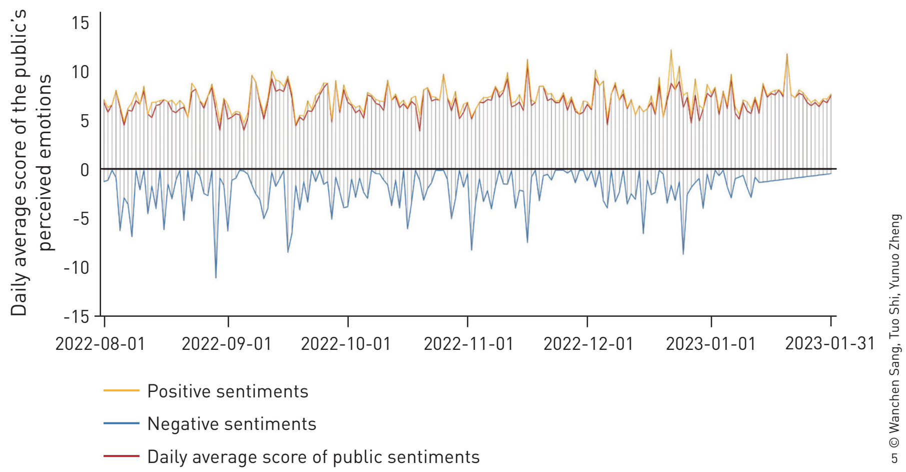
The changes of the daily average score of public sentiments are shown as Fig. 5. It found that although on certain dates (such as around September 1) the intensity of negative sentiments surpassed that of positive sentiments, the daily average score of public sentiment remained positive. This could be attributed to the fact that, despite the higher intensity of negative sentiments on those days, the number of positive sentiment posts far exceeded that of negative sentiment posts. This numerical disparity resulted in positive daily average scores even on days with stronger negative sentiments.

The study also visualized the daily average scores of public sentiments. The results indicate significant clusters of public

Table 3: Descriptive statistics of public sentiments

Variable	Mean	*SD*	Minimum	Maximum
Score of public sentiments	6.983	6.664	–22.600	65.896
Intensity of public sentiments	7.160	6.474	0.000	65.896



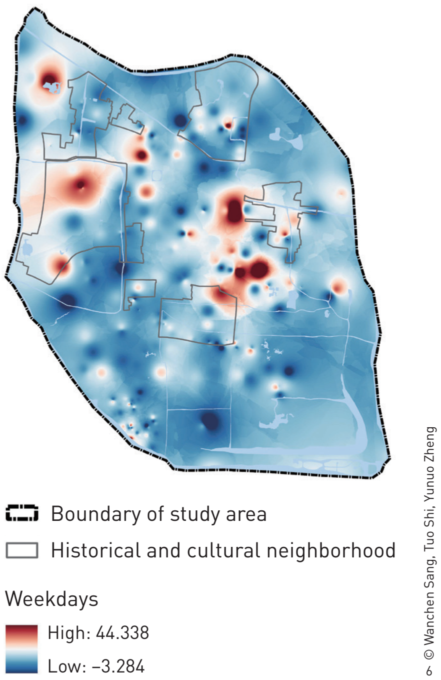


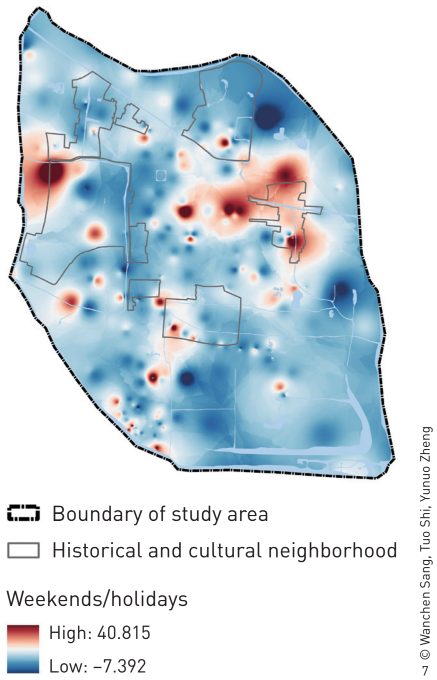
4. Analysis of the number of Weibo posts per day.
5. Analysis of the daily average score of public sentiments.

sentiments and a notable spatio-temporal heterogeneity between weekdays and weekends/holidays. Specifically, on weekdays, zones with stronger positive sentiments were mainly distributed around the entrance of ancient city on the Shangda Road in the northeastern part of the study area, the northern part of the Yuezi Town neighborhood, and along Jiefang Road; strong negative sentiments were found around the Wanghua Residential Community in the southern part of the study area, around the Jianhu-Xincun Residential Community in the southwestern part of the study area, and around the west side of the Former Residence of Calligraphy Sage neighborhood (Fig. 6). On weekends/holidays, stronger positive sentiments were primarily found in the northeastern corner of Yuezi Town neighborhood, Bazi Bridge neighborhood, and the western part of Lu Xun's Former Residence neighborhood; meanwhile, the negative sentiments were scattered around the

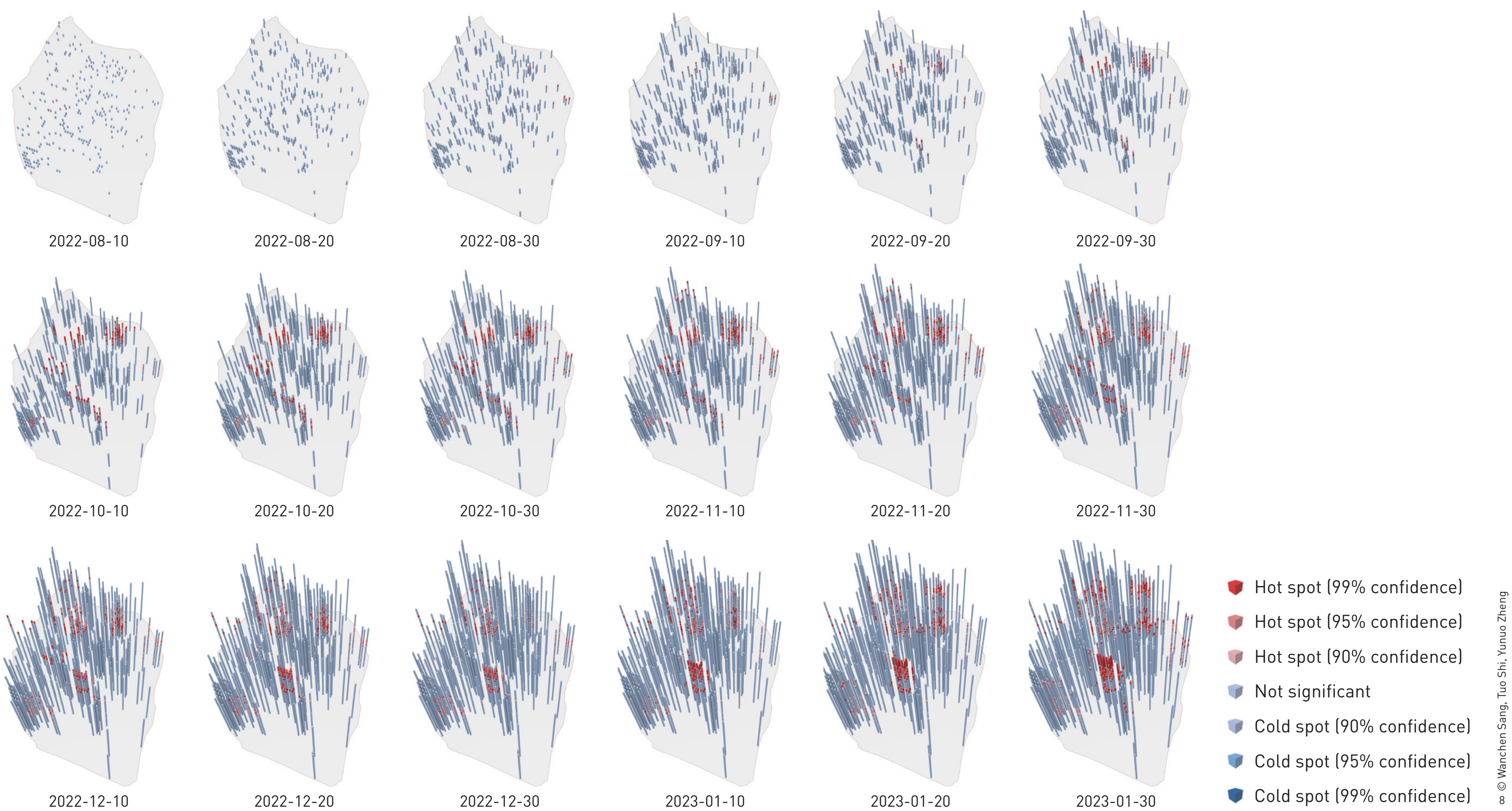
Wanghua Residential Community, the west side of the Former Residence of Calligraphy Sage neighborhood, and the Huayuan-Xincun Residential Community in the west (Fig. 7).

A hot and cold spot analysis of the Space-Time Cubes of daily public sentiments yielded 54,448 cube units, which were visualized using the ArcGIS Pro platform, with snapshots taken on the 10th, 20th, and 30th of each month (Fig. 8). The results showed that during August and September, 2022, stronger positive sentiment clusters first appeared in the Qianguan Alley neighborhood. Over time, the neighborhoods of Bazi Bridge and the Former Residence of Calligraphy Sage also showed significant clusters of stronger positive sentiments. As the National Day holiday approached, on September 30, the Lu Xun's Former Residence neighborhood and featured heritage sites like Shen Garden in the southern part of the study area exhibited more clustering of stronger positive sentiments. From October 1 to 10, other locations such as the Shimenkan neighborhood and the Jindi Intime City in the southwestern part of the study area also showed an increase of the hot spots of positive sentiments, aligning with the joy brought by holiday tourism. During November and December, the clustering of positive sentiments declined, concentrating in areas such as the





6. Spatial distribution of public sentiments on weekdays.
7. Spatial distribution of public sentiments on weekends/holidays.
8. Hot and cold spot analysis of public sentiments.



neighborhoods of Shimenkan, the Former Residence of Calligraphy Sage, and Lu Xun's Former Residence, and the entrance of ancient city on the Shangda Road. In early January 2023, although there was a noticeable rise of the clustering of positive sentiments, particularly around the Lu Xun's Former Residence neighborhood, public sentiments were negative overall.

6 Influencing Mechanism of HUL Characteristics on Public Sentiments

6.1 Selection of Influencing Factors

This study selected a total of 11 variables of HUL characteristics as explanatory variables from the dimensions of heritage intrinsic value, urban functional value, and urban landscape value, to explore its influencing mechanisms on public sentiments (Table 4).

1) Heritage intrinsic value: in this study, heritage level, heritage age, and natural asset value were selected as the evaluation indicators. Heritages within the study area were assigned values according to their protection levels—national (5), provincial (4), municipal (3), district (2), and ordinary buildings within the ancient city (1). Heritage age refers to the construction eras of the historical structures, with assigned values from 5 to 1 if the heritage was initially constructed earlier than the Tang Dynasty (before the year of 618), in Tang and Song Dynasties (618–1279), Yuan and Ming Dynasties (1271–1644), Qing Dynasty (1644–1911), and modern times, respectively. Natural asset value, the geographical and environmental foundation influencing the formation of the ancient city, was represented with the DEM (Digital Elevation Model) of the

Table 4: Explanatory variables for the impact of public sentiments

	Variable	Description	Source
Dependent variable			
	Score of public sentiments (weekday)	Score of public sentiments on weekdays	—
	Score of public sentiments (weekend/holiday)	Score of public sentiments on weekends/holidays	—
Independent variable			
Heritage intrinsic value	Heritage level	Assigned value of the level of heritage conservation units	Refs. [32][33]
	Heritage age	Assigned value of the age of heritage conservation units	Refs. [32][33]
	Natural asset value	DEM calculation of slope	Ref. [46]
Urban functional value	Building height	Overall height of the building (m)	Ref. [48]
	Internet popularity	Count of internet posts	Refs. [26][37]
	Density of recreational and entertainment facility	Distribution density of recreational and entertainment POI (per m^2)	Refs. [26][37][47]
	Density of medical service facility	Distribution density of medical service POI (per m^2)	Refs. [26][37][47]
	Density of transportation facility	Distribution density of transportation POI (per m^2)	Refs. [26][37][47]
Urban landscape value	Openness of water body	Area of water body (m^2)	Ref. [27]
	Openness of green space	Area of green space (m^2)	Ref. [27]
	Degree of mixed land use	$\sum P_i \ln(P_i)$ P_i is the area ratio of the land use type i to the grid	Refs. [27] [47]

terrain, referring to the research of Yuqi Lu et al.[46]: the variation of terrain relief defines the appearance of natural landscapes, where greater slopes are more likely to shape magnificent landscapes and smaller slopes may present gentle and pleasant sceneries.

2) Urban functional value: drawing from existing studies that use density, mix degree, and urban form to represent the built-up environment of a city[26][47][48], this study evaluated the urban functional value of HUL with indicators of building height, internet popularity, density of recreational and entertainment facility, density of medical service facility, and density of transportation facility.

3) Urban landscape value: considering the interwoven waterways in the Shaoxing ancient city , the study used indicators such as openness of water body, openness of green space[27], and degree of mixed land use[49] to measure the urban landscape value of HUL. This research adopted the measurement methods of urban landscape features by Lingqiang Kong et al.[27].

6.2 Analysis of Model Reliability

This study employed ArcGIS Pro analytical tools to perform the model credibility analysis on the scores of public sentiments on weekdays and weekends/holidays with the aforementioned 11 explanatory variables. Variables with a variance inflation factor (VIF) greater than 7.5 were excluded to eliminate the effects of multicollinearity. The maximum VIF value among the variables on weekdays was 1.42, and that on holidays was 1.30, indicating that the selected variables were reasonably selected.

The study performed a spatial autocorrelation test, yielding a global *Moran's I* index of 0.718 for the scores of public sentiments on weekdays, with Z-score of 113.469 ($P < 0.05$), passing the significance test. For weekends/holidays, the global *Moran's I* index was 0.812, with the Z-score of 171.508 ($P < 0.05$), also passing the significance test. These results indicate a spatially significant positive self-correlation of the scores of public sentiments.

Based on the above steps, the study constructed GWR models for weekdays and weekends/holidays and the preliminary results (Table 5) suggested a good fit of the models, demonstrating that both of them can effectively explain the variations in public sentiments.

6.3 Analysis of GWR Results

The regression coefficients for each variable in the GWR models are shown in Table 6 and Table 7. If both the mean and median values are positive, it indicates a positive effect of the explanatory variable on public sentiments; if both are negative, it indicates a negative effect.

For the intrinsic value, heritage level and heritage age both showed a significant positive correlation with public sentiments, indicating that heritages of higher protection levels and longer history would have a positive effect on public sentiments. However, natural asset value showed a negative effect on weekdays, possibly because on weekdays the public may prioritize work-related environmental factors, such as traffic convenience and proximity to workplaces, and they might put less attention to appreciating natural sceneries under daily work pressure.

In terms of urban functional value, compared with weekdays, recreational and entertainment facilities and medical service facilities had a weaker effect on weekends/holidays. This might be because the demand for urban functional features is not as much as weekdays. The negative effect of building height and internet popularity on public sentiments was also weaker on weekends/holidays, possibly indicating reduced attention to these HUL characteristics.

For the urban landscape value, the effect of the openness of water body and that of green space on public sentiments was relatively low on both weekdays and weekends/holidays, but this does not imply that these factors are not beneficial to the public's psychological health; instead, this may point to a more subtle influencing mechanism, where the aesthetic and recreational values of blue and green spaces may have a long-term, imperceptible positive effect on public sentiments. The degree of mixed land use showed a positive effect on weekdays but a negative effect on

Table 5: Results of GWR models

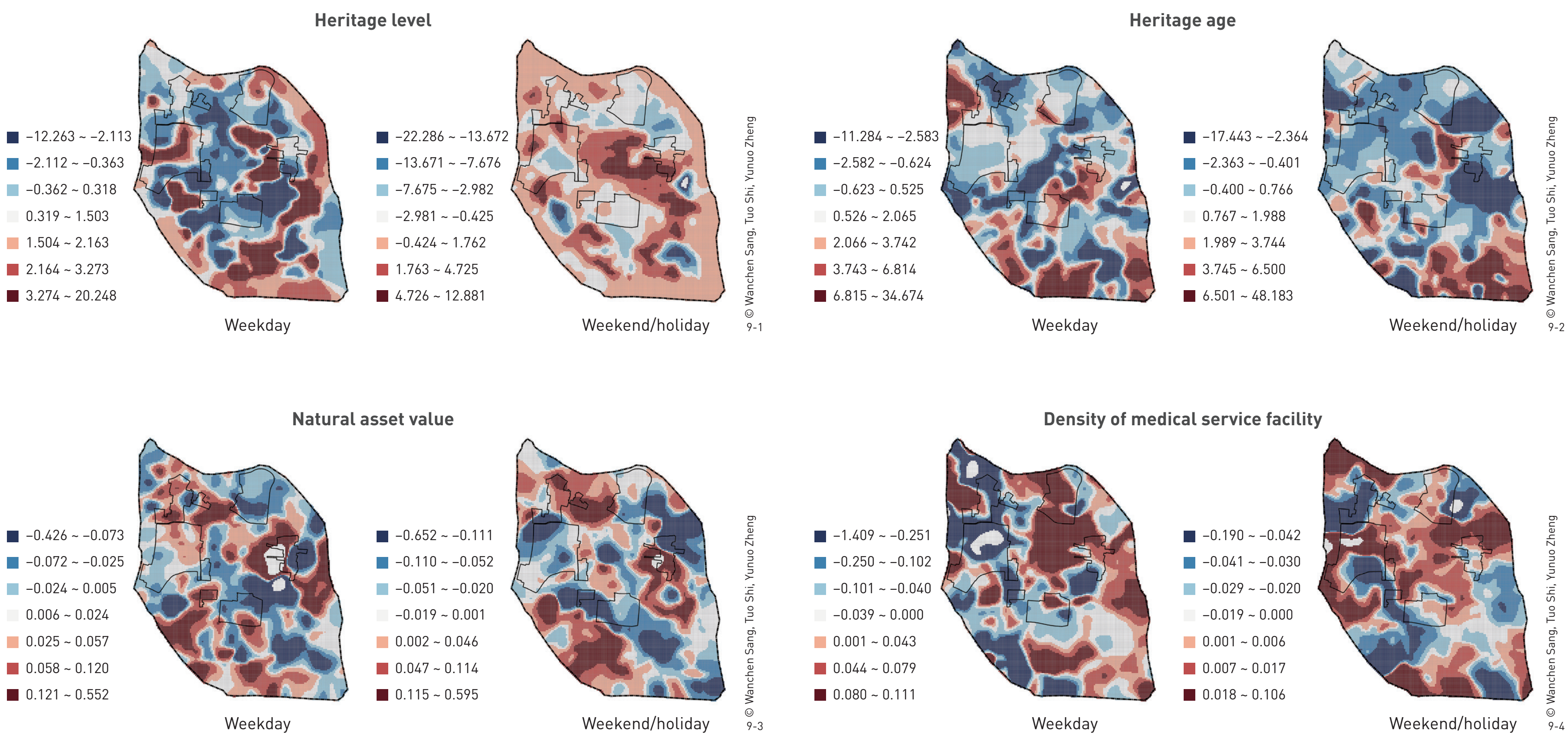
	R^2	R_{ADJ}^2	AIC	σ^2	*SD*	Pseudo-*t* statistics correction key values
Weekday	0.8753	0.8677	7163.8253	1.3706	1.2922	3.4140
Weekend/holiday	0.9014	0.8954	6836.8019	1.1835	1.1159	3.4134

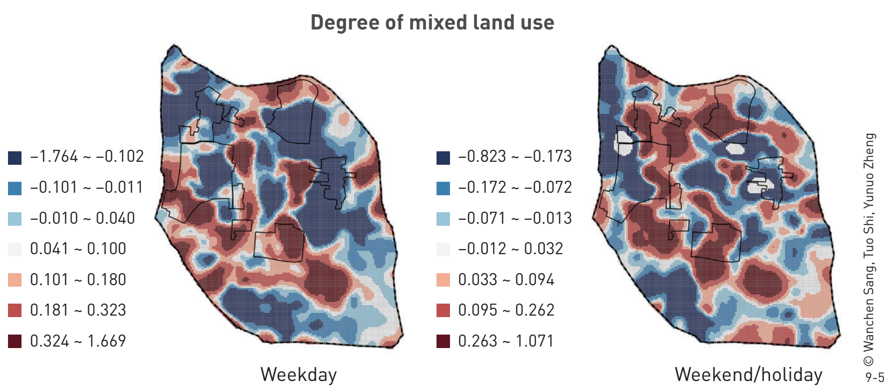
Table 6: Results of GWR model coefficients for public sentiments on weekdays

Explanatory variable		Mean	*SD*	Minimum	Median	Maximum
Heritage intrinsic value	Heritage level	0.7113	0.4162	−12.2628	0.6055	20.2484
	Heritage age	1.1873	0.5980	−14.9569	0.5463	34.6736
	Natural aesthetic value	0.0269	0.0377	−0.7311	0.0121	1.3360
Urban functional value	Building height	0.0010	0.0032	−0.0380	0.0001	0.0508
	Internet popularity (weekday)	0.0007	0.0005	−0.0458	0.0001	0.1445
	Density of recreational and entertainment facility	−0.0002	0.0048	−0.3938	0.0004	0.1557
	Density of medical service facility	−0.0876	0.0268	−1.4089	−0.0480	1.0971
	Density of transportation facility	0.0430	0.0169	−0.7531	0.0218	0.6314
Urban landscape value	Openness of water body	0.0005	0.0010	−0.0109	0.0004	0.0131
	Openness of green space	0.0001	0.0006	−0.0088	0.0001	0.0124
	Degree of mixed land use	0.0154	0.1506	−1.7635	0.0396	1.6686

Table 7: Results of GWR model coefficients for public sentiments on weekends/holidays

Explanatory variable		Mean	*SD*	Minimum	Median	Maximum
Heritage intrinsic value	Heritage level	0.0542	0.3853	−30.9836	0.0619	12.8814
	Heritage age	0.5094	0.5495	−27.6664	0.1342	48.1832
	Natural aesthetic value	−0.0059	0.0351	−0.6519	−0.0105	1.0412
Urban functional value	Building height	−0.0018	0.0029	−0.0692	−0.0008	0.1014
	Internet popularity (weekend/holiday)	−0.0016	0.0006	−0.0887	−0.0002	0.0772
	Density of recreational and entertainment facility	−0.0009	0.0044	−0.7486	0.0007	0.2605
	Density of medical service facility	−0.0147	0.0248	−1.8810	0.0048	1.5385
	Density of transportation facility	0.0081	0.0156	−0.7623	−0.0004	0.9051
Urban landscape value	Openness of water body	0.0004	0.0000	−0.0046	0.0001	0.0049
	Openness of green space	0.0005	0.0006	−0.0086	0.0001	0.0063
	Degree of mixed land use	−0.0034	0.1400	−1.6072	0.0068	1.0713





9. Spatio-temporal differentiation of the impact of five HUL characteristics on public sentiments.

weekends/holidays, suggesting that people might prefer simpler and more direct relaxing experiences during weekends/holidays, while areas with higher hybrid land use might lead to negative sentiments.

To further investigate the spatial heterogeneity of the explanatory variables' effects, the study ranked the explanatory variables based on their absolute value of the medians of regression coefficients, for both weekday and weekend/holiday GWR models. Five explanatory variables with relatively significant benefits on public sentiments on both models—heritage level, heritage age, natural asset value, density of medical service facility, and the degree of mixed land use—were identified, and the regression coefficient of each grid cell was visualized (Fig. 9).

1) Heritage level: 61.10% and 52.14% of the grid cells in the weekday and weekend/holiday GWR models, respectively, displayed positive regression coefficients, indicating a positive correlation between heritage level and public sentiments in these cells (i.e. leading to positive sentiments). On weekdays, this positive effect was mainly found around the neighborhoods of Yuezi Town, the Former Residence of Calligraphy Sage, and the Bazi Bridge, as well as the Shen Garden, which are the daily residential and recreational zones for the citizens. On weekends/holidays, it saw a significant increase in the number of grid cells where heritage sites were located showing a positive effect (Fig. 9-1); however, there was a noticeable difference in the regression coefficients of heritage level around the Lu Xun's Former Residence neighborhood between weekdays and weekends/holidays. The Lu Xun's Former Residence neighborhood, as a famous tourism destination that attracts the large number of visitors during weekends and holidays, showed a significant positive correlation between heritage level and public

sentiments, which locally reached up to 1.76. While, on weekdays, probably due to commercial activities or management regulation measures, the neighborhood showed a significant negative correlation between heritage level and public sentiments, which locally reached up to –12.26. This suggests that the HUL in this study area still needs to strike a balance between tourists' tourism demands and people's needs of daily commercial activities by, for example, taking flexible management measures on different days.

2) Heritage age: 60.85% and 52.15% of the grid cells in the weekday and weekend/holiday GWR models, respectively, exhibited positive regression coefficients, indicating a positive correlation between heritage age and public sentiments in these cells. This influencing pattern is similar to that of heritage level. On both weekdays and weekends/holidays, positive effects were concentrated in the Bazi Bridge neighborhood and several blocks in the southern part of the study area, where various cultural heritage sites spanning multiple historical periods sit. However, around the neighborhoods of the Former Residence of Calligraphy Sage, Yuezi Town, and Xixiao River, more grid cells with negative effects were found (Fig. 9-2). This might be because of the poor preservation status of those historical neighborhoods and the shortage of maintenance and supporting facilities, which would affect the visitors' experiences.

3) Natural asset value: 58.56% and 41.99% of the grid cells in the weekday and weekend/holiday GWR models, respectively, showed positive regression coefficients. On weekdays, typical Jiangnan water town landscape areas (such as Bazi Bridge neighborhood) and mountainous areas (such as the Yuezi Town neighborhood and Tashan Mountain scenic area) exhibited significant positive effects on public sentiments. However, during weekends and holidays, water town landscape areas still showed a significant positive effect, but the zones of mountainous landscapes showed a negative effect on public sentiments, possibly due to increased tourist traffic and crowded visiting experience (Fig. 9-3).

4) Density of medical service facility: 37.45% and 51.45% of the grid cells in the weekday and weekend/holiday GWR models, respectively, exhibited positive regression coefficients. Overall, the density of medical service facility showed a significant negative effect with public sentiments. However, in central areas of the ancient city, such as Zhongxing Middle Road and Guojin Joy City, where residential areas dominated, the density of medical service facility had a positive effect on public sentiments. This suggests that in densely populated residential areas, a reasonable distribution of medical service facilities can enhance positive public sentiments (Fig. 9-4).

5) Degree of mixed land use: 58.90% and 51.69% of the grid cells in the weekday and weekend/holiday GWR models, respectively, displayed positive regression coefficients. Areas such as the neighborhoods of the Lu Xun's Former Residence and Shimenkan, and Shen Garden showed positive effects on both weekdays and weekends/holidays. The neighborhoods of the Former Residence of Calligraphy Sage and Xixiao River also showed positive effects during weekends/holidays, demonstrating that for relaxing times multi-functional historical and cultural sites can effectively enhance the public's positive sentiments (Fig. 9-5).

7 Conclusions and Discussion

As an embodiment of a city's cultural heritages and historical memories, HUL can evoke collective emotional resonance and a sense of identity, thereby enhancing their happiness and satisfaction. Based on HUL and Emotional Geography theories, this study proposed the HCS analysis framework—consisting of three dimensions of heritage intrinsic value, urban functional value, and urban landscape value—and explored the spatio-temporal patterns of public sentiments and the influencing mechanisms of HUL characteristics on public sentiments in the Shaoxing ancient city. The results show that different HUL characteristics had played varied influencing mechanisms on public sentiments, and the effects of same HUL characteristics on public sentiments also vary between weekdays and weekends/holidays and among different HULs. On weekends/holidays, public sentiments were more influenced by the intrinsic value factors of HUL (e.g., heritage level, heritage age), whereas on weekdays, they were more affected by urban functional value factors (e.g., density of transportation facilities), and urban landscape value factors (e.g., degree of mixed land use) played a greater role in arousing people's positive sentiments.

It is important to note that the influence of HUL characteristics on public sentiments is not static. Urban designers should propose more targeted development planning and policies based on the local impact characteristics of HUL on public sentiments. This aligns with the core idea of HUL, which is to balance HUL preservation with urban development through comprehensive urban planning and management measures, thereby achieving a sustainable urban environment and enhancing people's well-being.

Despite the preliminary exploration of the relationship between HUL characteristics and public sentiments, this study has some limitations. First, existing research indicates that users who actively post information on social media platforms may be more inclined to make extreme or intense emotional expression[50]. This may result in a disparity between the expressed sentiments from the Weibo data with people's visiting experiences in real world. Future research need to combine with multiple data sources and methods, such as questionnaires and mobile application data, to obtain more comprehensive and more accurate data about the public's sentiments. Second, while this study examined HUL characteristics from the dimension of heritage intrinsic value, urban functional value, and urban landscape value, it is still challenging to fully capture the complexity and diversity of HUL. Future research could consider more potential influencing factors, such as socio-economic and individual factors, combined with relevant theories and technological methods, to better understand the influencing mechanisms of HUL characteristics on public sentiments. Additionally, the findings of this study are targeted to the Shaoxing ancient city. Future research is expected to conduct comparative studies with more cases in other regions, further verifying the universality and reliability of the findings. Simultaneously, continuous studies could also be conducted to track the long-term influencing mechanisms and evolutionary patterns of HUL characteristics on public sentiments in the Shaoxing ancient city.

Competing interests | The authors declare that they have no competing interests.

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历史性城市景观特征对公众情绪感知的影响机制及时空异质性研究——以中国浙江省绍兴古城为例

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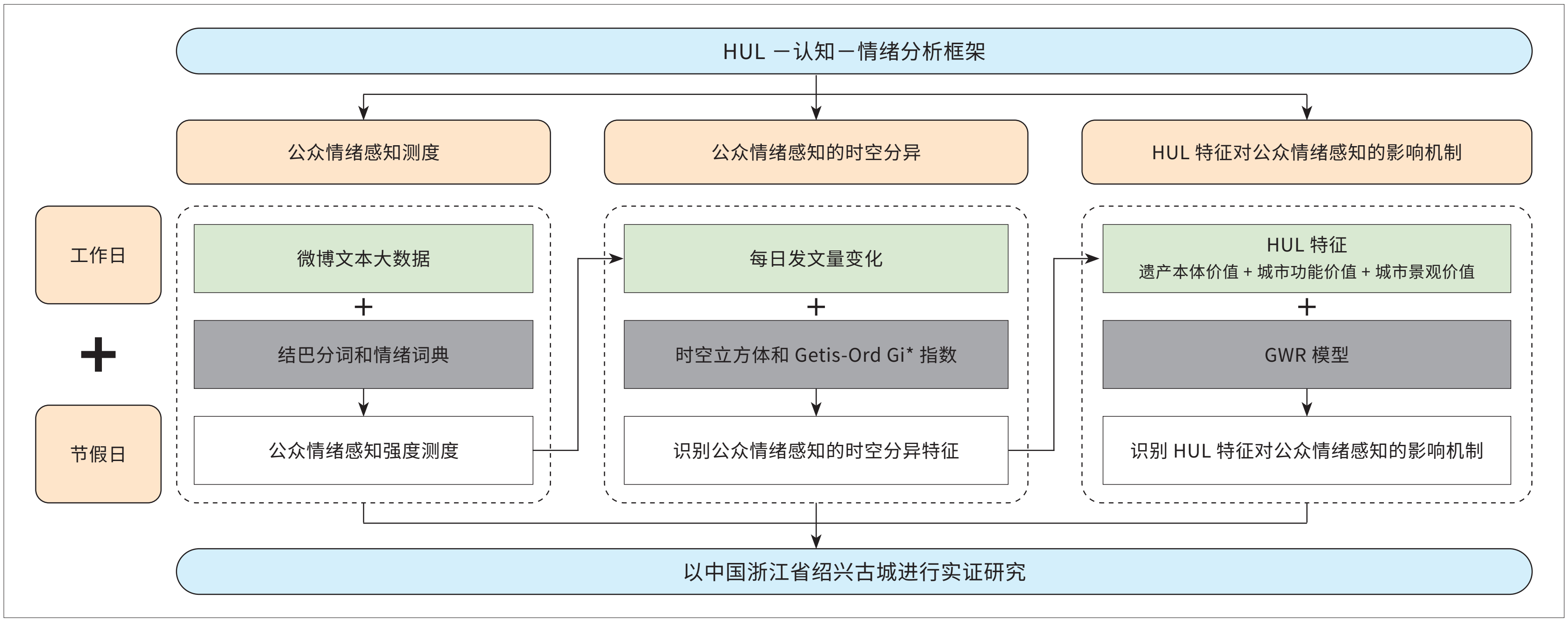
图文摘要



摘要

本文提出了“历史性城市景观－认知－情绪”分析框架，从历史性城市景观（HUL）遗产本体价值、城市功能价值和城市景观价值三个维度，结合语义分析、时空立方体等方法，通过中国绍兴古城案例，揭示了历史性城市景观环境特征对公众情绪感知的影响机制及其时空异质性。研究发现，不同的HUL特征对公众情绪感知的影响具有异质性；同一HUL特征在不同的时间（工作日与节假日）和空间中，对公众情绪的影响也表现出不同的模式。在节假日，公众情绪感知更受到与遗产本体价值相关的特征的影响，而在工作日，由于公众活动的性质发生变化，城市功能价值类特征对公众情绪的影响更加显著，城市景观价值对公众情绪感知的正面影响也更为突出。本研究旨在为提升公众在城市空间中的感知和情绪体验、识别历史城市的潜在空间改善机会提供科学参考。

关键词

历史性城市景观；公众情绪感知；时空异质性；微博数据；时空立方体；“历史性城市景观－认知－情绪”分析框架

文章亮点

- 首创性地提出“历史性城市景观－认知－情绪”分析框架，系统性地探究了历史城市景观特征对公众情绪感知的影响机制
- 从历史性城市景观遗产本体价值、城市功能价值和城市景观价值三个维度出发，揭示了公众情绪感知的时空分异特征
- 在节假日，公众情绪感知更受遗产本体价值类特征影响；在工作日，受城市功能价值和城市景观价值类特征的影响更加显著

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1 引言

2011年，联合国教科文组织颁布了《关于历史性城市景观的建议书》（以下简称“《建议书》”），提出了“历史性城市景观”（historic urban landscape，HUL）的理念，将之定义为“文化和自然属性历史层积的结果下，拥有两者价值的城市区域”[1]，强调了文化和自然的历史性层积，以及当前发展的动态叠合：文化是城市的动因，自然是城市的载体，而城市景观则是这种相互关系和演变的结果[1]。《建议书》中特别提到，在HUL保护中需要强调对公众集体记忆和普遍意识的调研[2]。情绪—认知理论指出，情绪是人与环境相互作用的产物[3]；近年的研究逐渐揭示了公众情绪感知的复杂性，证明公众情绪感知与HUL自身属性及遗产地形象[4]密切相关。

值得注意的是，古城或历史城市作为HUL的一个重要子类，近年来受到了越来越多的关注[5][6]。这些城市通常拥有丰富的历史和文化遗产，但也面临着全球化和现代化带来的各种挑战。其中，HUL的文化趋同和个性危机日益显著。这一问题的根本原因在于，急功近利的城市发展理念过度强调生产效率，却忽视了可持续发展中的人本需求和用户体验[7]。

近年来，公众对空间环境的感知和情绪体验也逐渐成为城市研究的焦点[8]，但将其与HUL相结合的探讨仍然较少。当前研究普遍从公众对HUL形象感知的角度出发，主要研究对象集中于基于数字足迹的HUL视觉形象感知[9]、基于网络评价的HUL价值[10]、遗产认同感知[11]等。然而，在以上研究中，公众情绪仅被视为HUL感知的衡量指标或表征，而其与HUL保护和可持续发展之间的关系尚未得到充分探讨。基于此，本研究提出“HUL—认知—情绪”的分析框架，特别关注历史城市HUL特征对公众情绪感知的影响机制，以期为提升公众幸福感、识别历史城市的潜在改善机会提供科学参考。

2 HUL视角下的公众情绪感知研究综述

2.1 HUL视角下的公众认知及其情绪感知

HUL不仅仅包含物理空间，也是文化和公众历史记忆的载体，更为人类当下的生活提供了深厚的背景和意义[12]；HUL还关注历史城市的无形价值，社会价值、社区身份和公民自豪感不仅存在于纪念构筑物中，还存在于集体生活的特定地点和时刻中[13]。在HUL视角下，人与所生活的地方能够产生深厚的情绪连接[14]。罗萨娜·博纳代等人指出，当公众接触HUL时，他们会基于自己的审美、情绪、文化和关系价值或与之相关的经验进行初步的感知评价[15]，例如历史学家可能强调HUL的起源问题，而建筑师则经常强调其艺术价值和特定材料的使用。在此背景下，理解公众对HUL的情绪感知，以及这种感知如何影响他们的情绪体验变得尤为关键。

自2001年“情绪地理学”（Emotional Geography）被正式提出[16]，“情绪开始摆脱作为纯粹主观精神问题的范畴而走向广阔的社会—文化空间，空间性、开放性和关系性的情绪也得到了确立”[17]。公众情绪作为人们对某公共事物或事件的集体情绪和态度，被视为“重复的地方互动和经验的产物”[18]；而感知则可反映公众对该公共事物或事件的认知程度。理查德·拉扎勒斯的情绪—认知理论进一步强调了认知与情绪之间的关系，他指出情绪是评估的产物[19]，这意味着通过感官接收能力和感性影响，公众对HUL的认知评估会直接影响他们的情绪。总的来说，认知是情绪产生的基础，情绪是认知的延伸[4]，公众对HUL的认知和情绪是一个动态的、互动的过程。为了更好地保护和利用HUL、确保HUL的规划和管理更加契合公众的需求和期望，需要深入了解公众对HUL的认知和情绪过程。

2.2 公众情绪感知的测度方法

随着位置服务技术的快速发展，可以通过感知设备和定位技术，主动或被动地获取、收集公众的情绪和态度信息，基于时空单元对公众情绪感知进行可视化测度。

主动测度方法通常需要公众的积极配合[20]，例如通过问卷调查[21]可以深入了解公众对某一特定城市景观的情绪反应；通过实验室观察[22]和穿戴感知设备[23]能够实时地捕获公众在城市空间中的情绪变化。这些方法为城市规划者提供了直接、深入的反馈，使其能够更好地理解公众的需求和期望。相较而言，被动测度方法则不需要公众主动配合[20]，借助词典或机器学习的大数据语义分析技术[24]，推特[25]、微博[26]等社交媒体数据为公众情绪感知的测度和可视化提供了新的机会。这些数据具有非结构化特性，且带有用户发布的空间位置信息，包含了大量反映城市居民真实情绪（例如快乐、悲伤、恐惧、厌恶、愤怒、惊讶等）的文本信息[27]，有助于揭示公众情绪感知的时空分布特征。这种方法已被广泛应用于城市规划中，如研究公共安全事件下的公众情绪[28]、恐怖事件下的公众对政府的情绪变化等[29]。

2.3 HUL特征对公众情绪感知的影响

HUL不是一个静态不变的建成环境，而是持续的动态层积的结果，是一个复杂、不断适应性演进的社会生态系统[30]。情绪受活动和场所的双重影响，而活动和场所的时空路径又受到情绪的影响和制约[31]，这意味着在不同的时间和空间中，公众对同一HUL的情绪感知可能存在显著的异质性。蹇嘉等人指出建成环境的物质特征、空间尺度和功能组织直接影响公众的情绪体验[31]。雷泽鑫等人的研究提供了一个理论框架，即HUL价值评价体系的准则层可以总结为“保护现状”“本体价值”和“城市结合度”三个方面[32]。

在本体价值层面，已有部分研究揭示了HUL本体价值如何影响公众

对历史城市的感知，凸显了它在建立情绪连接和培养文化认同中的核心作用。例如，有学者通过穿戴式设备对耶路撒冷的公众情绪感知进行调查，结果表明具有最高保护价值的圣殿山、旧城西墙遗址等地区分布着最高的公众积极情绪值[33]。此外，对于具有特定价值的景观遗产，如奥斯威辛集中营等黑色遗产地的公众情绪感知研究[34]也受到了学界的广泛关注。

然而，目前仍缺乏关于保护现状和城市结合度两个层面的公众情绪感知影响研究。从保护现状的角度看，城市中的历史建筑和遗址的保存状态也可能影响公众的身份认同和归属感，受到良好保护的历史遗迹可能会引发公众的自豪感和尊重，而被忽视或破坏的遗迹可能会引发失落或愤怒情绪[35][36]，但具体的影响机制仍缺乏探讨。从城市结合度的角度看，HUL与现代城市环境的融合程度可能会影响公众的情绪体验，这与城市地理学一直关注的建成环境的作用机制类似。单卓然等人通过采集武汉市主城区的POI和微博数据，证实了交通设施、商业网点、就业岗位、娱乐设施、公共服务设施，以及户外休闲场所的密度对居民情绪有显著影响[26]；米格尔・赫苏斯・梅迪纳—维鲁尔等人也证实了在西班牙乌韦达和巴埃萨城遗址周边的娱乐体验、设施便捷程度与游客积极情绪之间也存在显著正相关关系[37]；杨励雅等人发现，巴塞罗纳公众与情绪相关的推特推文更多聚集于旅游景点或休闲场所[18]。

总体而言，尽管城市被视为时空中的动态变化与累积叠加的产物，但HUL特征对公众情绪感知的影响机制仍缺乏探讨。本研究将基于社交媒体大数据对公众情绪感知进行测度，旨在揭示HUL特征对公众情绪感知的具体影响机制，为在城市规划和管理中识别历史城市中的潜在改善空间并予以优化提供理论和实践支撑。

3 HUL－认知－情绪分析框架构建

为了梳理从HUL特性的识别到公众情绪响应的动态演变过程，本研究构建了“HUL—认知—情绪”（HUL - Cognition - Sentiment，HCS）分析框架（图1）。该框架主要分为以下三个部分。

1）HUL特征分析。此部分借助地理加权回归（GWR）模型，揭示并分析HUL的核心特征维度，包括“遗产本体价值”“城市功能价值”和“城市景观价值”。遗产本体价值将遗产等级、遗产年代视为其保护现状和历史价值的体现；城市功能价值选择城市服务和遗产关注度来表征HUL与现代城市结构功能之间的互动关系；城市景观价值则以蓝绿空间开敞度、土地利用混合度来探讨HUL在视觉和审美层面上与自然和城市环境的融合程度。

2）公众情绪感知分析。此部分利用结巴分词和情绪词典分析微博文本大数据，将个体对HUL的直接反馈与深层次的认知体验结合起来，以实证量化从感官反应到情绪认知的转换过程：公众通过在识别HUL特征过程中的感官接收和感官体会，产生感官信息，感官信息经由大脑的复杂处理后形成认知，并表达为积极、中性或消极的情绪。

3）公众情绪感知时空分布分析。基于公众情绪感知测度结果，对公众工作日与节假日情绪的强度、地理分布进行对比研究，并通过时空立方体和Getis-Ord Gi*指数揭示情绪感知的时空分异特征，分析公众情绪感知的时空变化特征。人们的情绪感知决定着他们对HUL产生的主动或被动反馈，这些空间行为的集合也最终将动态影响HUL的形成和演变[38]——公众对HUL的反馈有两种主要形式：直接情绪表达和非情绪表现的空间行为。前者通过社交媒体等平台表达对HUL的喜爱或不满，可直接影响HUL的保护和发展策略；而后者（如频繁访问某处HUL）则可反映该HUL的公众吸引力，也将进一步影响城市规划和文化遗产管理。

综合这三个部分，HCS分析框架提供了一个可解释公众在HUL中的情绪感知产生过程的多维度视角。本研究将以中国浙江省绍兴古城为例，基于该分析框架和微博大数据，采用多种空间分析方法来深入探讨HUL特征与公众情绪感知之间的交互关系。

4 研究区域与研究方法

4.1 研究区域

浙江省绍兴古城建于公元前490年，已有2 500多年的建城史，是历史各时期不断演进形成的历史城区①，其范围为绍兴市越城区环城河外侧河沿以内的区域，面积约9km^2[39]，呈现“三山万户巷盘曲，百桥千街水纵横”的水城风貌，拥有丰富的历史文化遗存。根据《绍兴市历史文化名城保护规划（2021—2035年）》，古城包括八大历史文化街区（鲁迅故里、越子城、八字桥、书圣故里、西小河、石门槛、前观巷和新河弄），现有各级文物保护单位共62处（图2）。

研究基于Arcgis Pro平台，以20m × 20m为网格单元构建空间分析网络；研究时段为2022年8月1日至2023年1月31日，对工作日和节假日（包括法定节假日和周末休息日）进行差异化分析。

4.2 数据收集和处理

4.2.1 微博签到数据

微博签到数据指用户在微博平台上进行地理位置签到操作时产生的文本内容和时间信息等数据。研究采集了2022年8月1日至2023年1月31日研究区域内的微博签到数据，每条微博数据均包含用户ID、文本内容、发布时间、地理坐标等信息（表1）；在剔除重复、空白、不相关（如代购和房屋出租等）内容和无关网页链接后，最终获得8 151条有效签到数据。

① 信息来源：绍兴市人民政府官方网站。

4.2.2 HUL特征数据

HUL特征数据包括POI数据、历史遗产数据及遥感影像数据。POI数据主要涵盖休闲娱乐设施、交通设施和医疗服务设施，于2022年10月2~4日从高德地图上爬取。历史遗产数据包含研究区域内的文物保护单位的保护级别、建设年代和地理位置等信息，数据来源于《绍兴市历史文化名城保护规划（2021—2035年）》。研究从Google Earth采集了2021年6月12日当日空间分辨率为0.5m的遥感数据，以识别研究区域内的土地覆盖类型与空间格局：借助ArcGIS Pro平台，将研究区域内的土地覆盖类型划分为绿地、水域、裸地、建筑、道路和不透水表面6个类别，然后在每个类别中随机选择20~30个验证点进行验证。

4.3 研究方法

4.3.1 公众情绪感知测度

研究使用Python对微博签到数据中的文本信息进行情绪分析。首先，基于常用的结巴分词库[40]对每条文本信息进行分割，然后对每个词的出现频率进行统计；最后，研究采用开放数据源BosonNLP情感词典[41]来确定每条微博数据的情绪分数，该词典收录了约12万个情绪词条，每个词条都有对应的赋值（表2）。情绪的正负分值可分别反映情绪的性质，即积极、中性或消极情绪，而分数的绝对值则可反映情绪强度。研究结合签到数据中的地理位置信息，选择学界常用的反距离加权插值法[42]对每条微博测度后的情绪分数进行空间插值，从而获得研究区域内的公众情绪感知分布，其计算公式为：

$$\hat{Z}(X_j) = \sum_{i=1}^{N} \alpha_i Z(x_i), \tag{1}$$

式中：$\hat{Z}(X_j)$为j位置的情绪分数预测值，$Z(x_i)$为i位置的情绪分数测度值，α_i为预测j位置和已知i位置之间距离的倒数。

4.3.2 公众情绪感知时空分布测度

研究选择“时空立方体”的可视化方法来探究古城内公众情绪感知的时空分异特征。时空立方体是一种三维数据立方体，每个立方体单元都有固定的位置(x, y, t)，其中t表示时间步长，即前后两个时间点之间的差值；(x, y)表示其所在格网的空间位置[43][44]（图3）。本研究中，将时空立方体单元按照网格单元尺度划分（20m × 20m），时间步长设定为1天。

而后，研究选择Getis-Ord Gi*进行空间热点聚类分析，该指数能够反映某一区域内与周围区域的公众情绪感知程度之间的差异，从而识别出热点区域和冷点区域，即公众情绪感知高度聚集或者分散的区域，其计算公式为[43]：

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

式中，i代表某处的格网单元，j则是其邻域内的格网单元；x_j是格网单元j内的公众情绪感知分数均值；$w_{i,j}$是格网i和j之间的空间权重系数，采用ArcGIS Pro平台基于距离的默认算法计算，以测度公众情绪感知在空间上的关联；n代表所划分格网单元的总数量。Getis-Ord Gi*结果为正且显著时，其值越高，表明积极情绪聚类越紧密；当结果为负且显著时，其值越低，表示消极情绪聚类越紧密。

4.3.3 HUL特征对公众情绪感知的影响机制分析

研究使用GWR模型来分析绍兴古城HUL特征对公众情绪感知的影响机制。与传统的全局回归模型（如最小二乘法）相比，GWR模型可以有效解释回归系数的局部差异[45]，即能够对HUL特征与公众情绪感知在局

表 1：微博签到数据示例

用户	文本内容	发布时间	经度	纬度
A	“徐渭艺术馆算是一个在绍兴的惊喜了，有种快题照进现实的感觉，很喜欢的建筑。”	2022-08-12	120.574° E	29.998° N
B	“极致的热爱是无需刻意营造的！每天都在热爱的路上奔赴，眼里有光、照亮前方……”	2022-10-01	120.582° E	30.004° N
C	“走走停停就来了仓桥直街，很早很早时住了两年，每天闻着街头巷尾老头老太的交谈声醒来，人来人往热热闹闹的一条老街，现在开门了各种小店，小咖啡馆也散散落落的开着，有点韵味。”	2022-11-17	120.573° E	30.005° N
D	“孔乙己早就不是悲凉的化身了，反而成为茴香豆的带货网红了。”	2023-01-07	120.578° E	29.995° N

部地区的关系进行更精细化的分析，以精确识别哪些HUL特征能够显著影响公众情绪感知。其模型表达式为：

$$y_i = \sum_{j=1}^{k} \beta_k(u_i, v_i)\, x_{ij} + \varepsilon_i \,, \tag{3}$$

式中，y_i为时空立方体单元i处的公众情绪感知分数均值；（u_i, v_i）为单元i处的地理坐标；x_{ij}是单元i处公众情绪感知分数均值的第j个自变量值——在本研究中即为HUL特征变量，自变量的具体选择见第6章节；β_k (u_i, v_i) 为单元i处的第k个自变量的回归系数；ε_i为算法残差。

5 绍兴古城公众情绪感知时空异质性特征

分析结果显示（表3），绍兴古城内的公众情绪感知分数的均值为6.983，公众情绪感知强度的均值为7.160。这表明公众整体情绪感知的积极性较高，且消极情绪在整体上并不占据主导地位，说明研究区域内的公众更倾向于积极的情绪体验。

研究继而对公众微博发文数量和时间变化进行了详细分析，发现在2022年10月初和2023年1月末（即国庆节期间和春节前夕），微博发文量出现了明显高峰；而2022年12月底出现了显著的低谷，这与中国在该时期的疫情相关，健康风险可能导致了公众外出和社交媒体使用的减少；其他月份的发文量波动相对较小。同时，结果显示，节假日的发文数量要显著高于工作日（图4）。

研究区域内每日公众情绪感知分数的均值变化如图5所示。研究发现，虽然在某些日期（如9月1日前后）消极情绪的强度超过了积极情绪，但当日的公众情绪感知分数均值仍然为正。造成此现象的原因可能是积极情绪的发文数量远超过消极情绪的发文数量，这种数量上的差异导致即使在消极情绪强度较高的日子，整体的情绪感知分数均值仍为正值。

研究进而将每日的公众情绪感知分数均值进行可视化表达，结果表明，公众情绪感知呈现出显著的积聚性特征，且工作日和节假期的公众情绪感知呈现出明显的时空异质性。具体而言，工作日的高强度积极情绪主要分布在研究区域内东北部的上大路古城入口、越子城街区北部和中部解放路沿线附近；高强度消极情绪主要分布在研究区域内南部望花小区附近、西南部的鉴湖新村附近，以及书圣故里街区西侧附近（图6）。而节假日的高强度积极情绪主要分布在东北方向的越子城东北角、西北方向八字桥街区及中部鲁迅故里街区西侧附近；高强度消极情绪主要分布在望花小区附近、书圣故里西侧，以及西部的花园新村附近（图7）。

研究通过对每日公众情绪感知时空立方体进行冷热点分析，得到54 448个计算结果，而后借助ArcGIS Pro平台对其进行可视化，并选择

表 2：BosonNLP 情绪词典中部分词语赋值示意

类型	词语	赋值
正向词	知足	2.1
	开心	2.6
	幸福	2.6
	浮云	0.8
负向词	狂躁	−4.4
	扰民	−6.5
	救命	−4.1
	无良	−4.1
中性词	按照	0.0
	现象	0.0
	南区	0.0
程度副词	不得了	1.8
	非常	1.8
	一点	0.7
停用词	也、于是、另外	删除，不计算分数

注
研究直接使用 BosonNLP 文本词典中的赋值。

表 3：公众情绪感知的描述性统计

变量	描述	均值	标准差	最小值	最大值
公众情绪感知分数	正值表示积极情绪，负值表示消极情绪	6.983	6.664	−22.600	65.896
公众情绪感知强度	公众情绪感知分数的绝对值	7.160	6.474	0.000	65.896

每月10日、20日、30日进行展示（图8）。分析结果显示，在2022年8~9月，高强度积极情绪积聚区首先出现在古城中部的前观巷街区。随着时间推移，在古城东北方向的八字桥和书圣故里街区也出现了明显的高强度积极情绪积聚。随着国庆假期的临近，在9月30日，鲁迅故里街区和东南部的沈园等重要历史文化遗产点附近出现高强度积极情绪积聚分布；10月1~10日，石门槛街区、西南部的金帝银泰城等位置同样呈现积极情绪积聚逐渐增多。11~12月期间，积极情绪的积聚逐渐减少，但仍然分布于石门槛、鲁迅故里、书圣故里街区，以及上大路古城入口等地。2023年1月上旬，积极情绪的积聚性明显抬升，以鲁迅故里街区最为明显，但结合图7的公众情绪感知空间分布来看，整体仍以消极情绪为主。

6 HUL特征对公众情绪感知的影响机制

6.1 影响因素的选取

研究从HUL遗产本体价值、城市功能价值和城市景观价值三个维度选取了共11个HUL特征变量作为解释变量，以对HUL特征对公众情绪感知的影响机制作进一步探讨（表4）。

1）遗产本体价值：研究选择遗产级别、遗产年代和山水价值作为评价指标。遗产级别是按照国家历史文化遗产保护规范，将全国重点、省级、市级、区级文物保护单位和古城内普通建筑分别赋值5~1；遗产年代指历史遗产建造年代的时间范围，对唐代以前、唐宋、元明、清代及近现代的建筑分别赋值5~1；山水价值是影响古城形成的重要地理环境基底，本文借鉴陆玉麒等人的研究[46]，选择地形DEM作为表征：地形地势的起伏变化可以提供变化多样的山水景观，较大坡度更易呈现出雄伟壮观的景观，较小坡度则可能呈现出柔和宜人的景色。

2）城市功能价值：借鉴既有研究中使用密度、混合度和城市形态等城市建成环境的表征方法[26][47][48]，本研究以建筑高度、打卡关注度、休闲娱乐设施密度、医疗服务设施密度及交通设施密度来评价HUL的功能价值。

3）城市景观价值：考虑到绍兴古城内水网纵横交错的“水城”特点，研究使用水域空间开敞度、绿地开敞度[27]和土地利用混合度[49]进行表征，具体方法借鉴孔令强等人对城市景观特征的测度方法[27]。

6.2 模型可信度分析

本文运用ArcGIS Pro分析工具，分别对研究区域内工作日和节假日的公众情绪感知分数与上述11个解释变量进行模型可信度分析。剔除方差膨胀因子（VIF）大于7.5的变量来消除多重共线性的影响后，其中工作日中各变量的最大值为1.42，节假日中变量的最大值为1.30，表明本文所选取的变量不存在共线性关系，指标选取合理。

其次，工作日公众情绪感知分数的全局*Moran's I*指数为0.718，*Z*值为113.469（$P<0.05$），通过显著性检验；节假日公众情绪感知分数的全局*Moran's I*指数为0.812，*Z*值为171.508（$P<0.05$），通过显著性检验，说明研究区域内公众情绪感知分数在空间上存在显著自相关。

在此基础上，研究构建了工作日和节假日的GWR模型，模型初步结果（表5）显示模型的拟合程度较好，说明两个模型能够较好地解释公众情绪感知的影响变化。

6.3 GWR结果分析

工作日和节假日GWR模型中各变量的回归系数分别如表6和表7所示。如果均值和中位数均为正值，说明解释变量对公众情绪感知存在正向影响；如果均值和中位数均为负值，说明解释变量对公众情绪感知存在负向影响。

在遗产本体价值上，遗产级别和遗产年代与公众情绪感知分数呈现显著正相关性，这意味着较高级别、历史更悠久的遗产会对公众情绪感知产生积极影响。然而，山水价值在工作日中呈现负相关效应，可能是因为在工作日公众更加注重与工作相关的环境要素，如交通便捷性、工作地点近邻性等因素。在日常工作压力下，人们可能会将自然美景的欣赏置于较低的优先级。

在城市功能价值上，与工作日相比，节假日休闲娱乐设施和医疗服务设施的影响较弱，这可能是因为节假日期间人们对城市功能性特征的需求不如工作日紧迫。建筑高度和打卡关注度对公众情绪感知的负向影响也较弱，可能表明节假日人们对这些HUL特征关注度降低。

在城市景观价值上，水域空间开敞度和绿地开敞度在工作日和节假日对公众情绪感知的影响程度都较低，但这并不意味着它们对人们的心理健康无益。这可能指向一个更细微的影响机制，即蓝绿空间的审美和休闲价值可能会在潜移默化中对公众情绪感知产生积极效应。而土地利用混合度在工作日呈现正相关效应、在节假日中却呈现负相关效应。这表明，在节假日期间，人们可能更倾向于单一而直接的放松体验，用地类型混合度较高的地区则可能导致公众产生负面情绪。

为了进一步探究各解释变量效应的空间异质性，研究将各项解释变量在工作日和节假日GWR模型中的回归系数中位数的绝对值按照大小排序，选择在工作日和节假日对公众情绪感知影响都较显著的5个解释变量——遗产级别、遗产年代、山水价值、医疗服务设施密度和土地利用混合度——分别对各网格单元的回归系数进行可视化（图9）。

1）遗产级别：在工作日和节假日GWR模型中，各有61.10%和52.14%的格网单元展示出正向回归系数，即这些格网单元的遗产级别与公众情绪感知呈现正相关（积极情绪）。工作日期间，正相关效应主要出现于越子城街区、书圣故里街区、八字桥街区附近，以及沈园等地段，这些是居民日常居住和休闲的主要区域。在节假日期间，各街区和文物保护单位所在格网单元内出现的正相关效应显著增加（图9-1）。但

表 4：公众情绪感知影响变量

变量		描述	参考文献
因变量			
	情绪分数（工作日）	工作日内的情绪感知分数	—
	情绪分数（节假日）	节假日内的情绪感知分数	—
自变量			
遗产本体价值	遗产级别	文物保护单位的级别赋值	参考文献 [32][33]
	遗产年代	文物保护单位的年代赋值	参考文献 [32][33]
	山水价值	DEM 计算坡度	参考文献 [46]
城市功能价值	建筑高度	建筑物的整体高度（m）	参考文献 [48]
	打卡关注度	签到次数	参考文献 [26][37]
	休闲娱乐设施密度	休闲娱乐 POI 分布（个 / m^2）	参考文献 [26][37][47]
	医疗服务设施密度	医疗服务 POI 分布（个 / m^2）	参考文献 [26][37][47]
	交通设施密度	交通设施 POI 分布（个 / m^2）	参考文献 [26][37][47]
城市景观价值	水域空间开敞度	水域空间面积（m^2）	参考文献 [27]
	绿地开敞度	绿地面积（m^2）	参考文献 [27]
	土地利用混合度	$\sum P_i \ln(P_i)$ P_i 是第 i 中土地利用类型的面积占格网面积的比值	参考文献 [27] [47]

在鲁迅故里街区附近，遗产级别的回归系数在工作日和节假日的差异较大。节假日时，鲁迅故里街区因大量慕名而来的游客到访，遗产级别与公众情绪感知之间呈现显著的正相关效应，局部最高可达1.76；在工作日，可能由于商业化活动或管制措施，该地区的遗产级别与公众情绪感知呈现出显著的负相关效应，局部可达到–12.26。这表明研究区域内的HUL在吸引游客与满足日常商业活动之间仍需要平衡，在不同的时段采取灵活的管理措施。

2）遗产年代：在工作日和节假日GWR模型中，各有60.85%和52.15%的格网单元具有正回归系数，即这些格网单元的遗产年代与公众情绪感知呈现正相关，这与遗产级别的影响比较相似。在工作日和节假日期间，正相关效应主要集中于八字桥街区和研究区域南部的部分地段，这些地区拥有跨多个历史时期的各种文化遗产。然而，书圣故里、越子城和西小河等街区在工作日和节假日则以负相关效应的格网单元居多（图9–2），可能因以上区域的文化遗产保护状况不佳，缺乏适当维护、配套设施匮乏等影响公众的情绪体验。

表 5：GWR 模型结果

	R^2	$R_{ADJ}{}^2$	AIC	σ^2	标准差	伪 t 统计数据校正关键值
工作日	0.8753	0.8677	7163.8253	1.3706	1.2922	3.4140
节假日	0.9014	0.8954	6836.8019	1.1835	1.1159	3.4134

表 6：工作日公众情绪感知的 GWR 模型系数计算结果

	解释变量	均值	标准差	最小值	中位数	最大值
遗产本体价值	遗产级别	0.7113	0.4162	–12.2628	0.6055	20.2484
	遗产年代	1.1873	0.5980	–14.9569	0.5463	34.6736
	山水价值	0.0269	0.0377	–0.7311	0.0121	1.3360
城市功能价值	建筑高度	0.0010	0.0032	–0.0380	0.0001	0.0508
	打卡关注度（工作日）	0.0007	0.0005	–0.0458	0.0001	0.1445
	休闲娱乐设施密度	–0.0002	0.0048	–0.3938	0.0004	0.1557
	医疗服务设施密度	–0.0876	0.0268	–1.4089	–0.0480	1.0971
	交通设施密度	0.0430	0.0169	–0.7531	0.0218	0.6314
城市景观价值	水域空间开敞度	0.0005	0.0010	–0.0109	0.0004	0.0131
	绿地开敞度	0.0001	0.0006	–0.0088	0.0001	0.0124
	土地利用混合度	0.0154	0.1506	–1.7635	0.0396	1.6686

表 7：节假日公众情绪感知的 GWR 模型系数计算结果

	解释变量	均值	标准差	最小值	中位数	最大值
遗产本体价值	遗产级别	0.0542	0.3853	–30.9836	0.0619	12.8814
	遗产年代	0.5094	0.5495	–27.6664	0.1342	48.1832
	山水价值	–0.0059	0.0351	–0.6519	–0.0105	1.0412
城市功能价值	建筑高度	–0.0018	0.0029	–0.0692	–0.0008	0.1014
	打卡关注度（节假日）	–0.0016	0.0006	–0.0887	–0.0002	0.0772
	休闲娱乐设施密度	–0.0009	0.0044	–0.7486	0.0007	0.2605
	医疗服务设施密度	–0.0147	0.0248	–1.8810	0.0048	1.5385
	交通设施密度	0.0081	0.0156	–0.7623	–0.0004	0.9051
城市景观价值	水域空间开敞度	0.0004	0.0000	–0.0046	0.0001	0.0049
	绿地开敞度	0.0005	0.0006	–0.0086	0.0001	0.0063
	土地利用混合度	–0.0034	0.1400	–1.6072	0.0068	1.0713

3）山水价值：在工作日和节假日GWR模型中，各有58.56%和41.99%的格网单元具有正回归系数。在工作日，八字桥街区、越子城街区和塔山等地段作为江南水乡和山川的特色景观，对公众情绪感知呈现明显正相关效应。然而，节假日期间，拥有大量水乡景观的八字桥街区呈现正相关效应；越子城、塔山等区域的山川景观对公众情绪感知呈现负相关效应，这或许与节假日期间旅游人流量增多、景观体验受限有关（图9-3）。

4）医疗服务设施密度：在工作日和节假日GWR模型中，各有37.45%和51.45%的空间单元具有正回归系数。整体上，医疗服务设施密度与公众情绪感知呈现显著的负相关效应，但在古城中部的中兴中路、国金大悦城等本地居住区，医疗服务设施密度与公众情绪感知呈现正相关效应。这表明对于居住区比较集中的区域来说，医疗服务设施的合理分布能够提高居民的积极情绪（图9-4）。

5）土地利用混合度：在工作日和节假日GWR模型中，各有58.90%和51.69%的空间单元具有正回归系数。鲁迅故里和石门槛街区、沈园等地段在工作日和节假日期间均呈现正相关效应，书圣故里和西小河街区在节假日期间也呈现正相关效应，这说明对于节假日的公众来说，多功能的历史文化场所能够有效提高积极情绪（图9-5）。

7 结论与讨论

HUL作为城市的文化遗产和历史记忆的集中体现，可以激发公众的情绪共鸣和认同感，从而提高公众的幸福感和满意度。本研究基于HUL和情绪地理学理论，提出了“HUL—认知—情绪”分析框架，并从HUL遗产本体价值、城市功能价值和城市景观价值三个维度，对绍兴古城内公众情绪感知时空特征，以及HUL特征对公众情绪感知的影响机制进行了综合分析。结果表明，不同的HUL特征对公众情绪感知的影响具有异质性，即使是同一HUL特征在不同的时间（工作日与节假日）和空间中，对公众情绪的影响也表现出不同的模式。具体来说，在节假日，公众情绪感知更受到与遗产本体价值相关的特征（如遗产年代、遗产级别）的影响。而在工作日，由于公众活动的性质发生变化，城市功能价值类特征（如交通服务设施密度）对公众情绪的影响变得更加显著。此外，城市景观价值类特征（如土地利用混合度）在工作日对公众情绪感知的正面影响也更为突出。

需要注意的是，HUL特征对公众情绪感知的影响并非是一成不变的，城市设计者应结合公众情绪感知影响效应的局部特征，提出更有针对性的建成环境规划和政策。这与HUL的核心思想相契合，即通过综合的城市规划和管理措施，平衡HUL保护与城市发展的关系，从而实现可持续的城市环境，并提升公众福祉。

尽管本研究对HUL特征与公众情绪感知的关系进行了初步探索，但仍存在一定局限性。首先，有研究表明，在社交媒体平台上主动发布信息的用户，可能更倾向于表达极端或强烈的情绪状态[50]，这种倾向可能致使本研究采用的源自微博数据的情绪感知可能与公众在实际HUL游览体验存在一定差异。未来的研究可结合其他数据源和方法，例如问卷调查和移动应用数据，以获取更全面、更准确的公众情绪信息。其次，本研究选择遗产本体价值、城市功能价值和城市景观价值等来表征HUL特征，虽具有一定的代表性，但仍难以全面表征HUL的复杂性和多样性。未来研究可结合相关理论和技术手段，考察其他可能影响公众情绪的因素（如社会经济因素和个体特征），以更全面地理解HUL特征对公众情绪感知的影响机制。此外，本研究的影响分析结果仅限于绍兴古城这一特定地区，未来研究可拓展研究范围和方法，进行跨地区的横向比较，进一步验证研究结果的普适性和可靠性；同时，可考虑进行纵向研究，追踪绍兴古城HUL特征和公众情绪感知的变化趋势，以揭示其长期影响机制和演变模式。